

Request for Specific Services 2016 85 02 for the implementation of Framework Contract EAHC/2013/CP/04

Final report

and Consumers







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GLOSSARY

Terminology abbreviations

CPA Consumer Protection Authorities

DPA Data Protection Authorities

DSM Digital Single Market

EAA European Advertising Alliance

GDPR General Data Protection Regulation

JRC Joint Research Center

KPI Key Performance Indicators

OFT UK Office of Fair Trading (note: closed down in April 2014 and responsibilities were passed to the Competition and Market Authority (CMA) and Financial Conduct Authority (FCA))

OTT Over-the-Top communication services

UCPD Unfair Commercial Practices Directive

WTP Willingness-to-pay

Country codes

BE Belgium LU Luxembourg

BG Bulgaria HU Hungary

CZ Czech Republic MT Malta

DK Denmark NL Netherlands

DE Germany AT Austria

EE Estonia PL Poland

IE Ireland PT Portugal

EL Greece RO Romania

ES Spain SI Slovenia

FR France SK Slovakia

HR Croatia FI Finland

IT Italy SE Sweden

CY Cyprus UK United Kingdom

LV Latvia IS Iceland

LT Lithuania NO Norway

Abstract

This consumer market study about personalised pricing/offers in the EU looks at: the nature and prevalence of the online personalised practices used by sellers/providers; whether businesses are transparent about online personalisation; consumers' awareness and perception of online personalised practices and problems experienced; and the economic value/effects of personalised pricing/ranking of offers.

The study covers all EU Member States, Iceland and Norway. Between December 2016 and November 2017, the following tasks were carried out: a review of the literature on online personalised practices; consultations with consumer and data protection authorities, national experts and business operators; an assessment of the applicable EU Regulatory framework and sellers' awareness and compliance with this legislation; an assessment of the economic effects of personalised pricing/ranking of offers; an online survey measuring consumers' awareness of/opinions on such practices; a mystery shopping exercise (in four markets, namely airline tickets, hotels, sports shoes and TVs) replicating 'real life' experiences when searching for goods/services on e-commerce websites, designed to assess the prevalence of personalised pricing/ranking of offers; and an online behavioural experiment designed to assess consumers' ability to recognise online personalisation, as well as their "willingness to purchase" personalised products, depending on the level of transparency in communication.

1. Background, introduction and research objectives

1.1. Introduction and background of the study

The topic of the consumer market study on online market segmentation through personalised pricing/offers in the EU is linked to one of the ten top priorities of the European Commission, 'the Digital Single Market' (DSM). The Digital Single Market is defined as a market in which the free movement of goods, persons, services and capital is ensured and where both individuals and businesses can access and exercise online activities under conditions of fair competition and benefit from a high level of consumer and personal data protection, irrespective of their place of residence and nationality¹.

The DSM Strategy, adopted in May 2015, aims to bring down the market barriers to a seamless online experience for businesses and individuals across Member States by means of taking advantage of the rapid advance of new digital technologies on the online market. To this end, the Strategy encompasses sixteen initiatives and targets three policy areas (pillars):

- First pillar "Better access for consumers and businesses to online goods and services across Europe": helping to make the EU's digital world a seamless and level marketplace to buy and sell;
- Second pillar "Creating the right conditions for digital networks and services to flourish": designing rules which match the pace of technology and support infrastructure development; and
- Third pillar "Maximising the growth potential of our European Digital Economy": ensuring that Europe's economy, industry and employment take full advantage of the potential of digitalisation.

¹ Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions, (2015), "A Digital Single Market Strategy for Europe". Available at: http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52015DC0192&from=EN

The objectives of the current study can also be understood in the context of the three pillars.

In the first pillar, the DSM Strategy highlights that a common set of cross-border e-commerce rules should be ensured. This is of particular relevance to this study as it will facilitate online sales and purchases and will enhance consumers' trust by enforcing the existing consumer protection rules in the digital realm². In addition, certain practices like unjustified geo-blocking that result in denial or block of access to websites and lower consumer choice would be prevented. The second pillar of the strategy addresses another essential aspect of the e-commerce digital ecosystem, online platforms. The strategy recognises the advantages in terms of efficiency, increased consumer choice, stimulated economic growth and innovation that platforms such as "search engines, social media, e-commerce platforms, app stores, price comparison websites" bring to consumers and businesses. However, it also calls for a stronger regulatory framework to resolve issues related to the lack of transparency in the process of data collection, use of data and pricing practices. Consequently, in the second pillar, the strategy highlights the importance of security and trust in the market for its success and the need for **stronger data protection rules**.

Finally, the third pillar of the DSM strategy seeks **to maximise digital growth** through investment in technologies such as cloud computing and Big Data. For example, it announced the intention to launch a 'Free Flow of Data initiative' in order to deal with "restrictions on the free movement of data for reasons other than the protection of personal data".³ Given the fact that the digital economy is largely data-driven, the free movement of data in the emerging digital ecosystem is essential for boosting e-commerce and innovation across the EU and concerns all types of business relationships (e.g. B2B, B2C, machine-to-machine). A review of the most recent EU legislation that is applicable to the online environment is presented in Annex 2⁴.

The current study focused specifically on the case of the segmentation of online markets through personalised pricing and offers by online firms⁵, following the advance in data gathering and processing techniques (e.g. via the use of cookies), which have allowed companies to embrace innovative marketing strategies, based on personalisation. The possibility of tracking and profiling consumer behaviour enables online firms to possibly apply "personalised pricing" (i.e. charge a different price to different people for the same good or service), "personalised ranking of offers"⁶ (i.e. provide different results when consumers search for the same products online), and "targeting of online advertising" (i.e. a way of personalising advertising based upon information about activities such as previous web browsing). In the course of this study, the use of the term personalised pricing/offers relates to any of the three aforementioned personalised practices. The study explored these practices (see the detailed definition of all personalisation practices in Section 1.4: Terminology) from the following perspectives:

- their prevalence on the European market;
- the advantages they could bring for consumers and business operators alike, and:
- the disadvantages and issues related to consumer concerns linked to, for example, transparency and data privacy that consumers might encounter.

It was intended that the evidence from the study could lead to better enforcement of existing competition and consumer protection rules and would examine the possibility that

² Digital Market Strategy Communication referenced above¹

³ Digital Market Strategy Communication referenced above¹

⁴ Also how these may apply to personalisation practices

⁵ E-commerce websites, including marketplaces and those online sellers that may also have an offline activity, as well as search engines and comparison tools. Excluded are practices encountered in other environments such as online social media.

⁶ Or else personalised offers or price steering (the latter often encountered in scientific publications)

the data feed into a follow up initiative to the fitness check of the EU consumer and marketing law⁷, in case the evidence was strong enough.

1.1. Objectives and scope of the study

In December 2016, the European Commission commissioned a consumer market study on online market segmentation through personalised pricing/offers in the European Union with the aim to:

- 1) Identify the main personalisation practices by online sellers and providers in the European online market and their impact on consumers. In order to do this, the study had to:
 - Identify the means for collecting consumers' data and the way this data is used by online sellers/providers for personalisation of their services and offers
 - Assess the level of consumers' awareness and understanding of such practices and the different means by which information is communicated to them
 - Identify the main challenges that consumers encounter, especially those related to transparency of personalisation practices, data protection and privacy and unfair commercial practices.
- 2) Assess online sellers and providers' level of awareness and compliance with EU and national legislation when it comes to personalised practices, to the extent this was possible considering the limited feedback regulators are able to provide on the topic (the limitations are explored later in this report).
- 3) In case there was sufficient evidence: Assess the economic value and detriment of personalised practices for consumers and online sellers/providers via economic modelling and how the costs/benefits are divided between them

The current study addressed these objectives via the following tasks:

Main Task 1 – Overall analysis of the nature and prevalence of personalised pricing/offers practices for EU consumers. Task 1 provided the analytical framework on which the research and reporting was based. It encompassed desk research including a literature review, research of primary sources through a business operators' survey and a targeted stakeholder consultation, and provided an overview of the regulatory framework. In addition, Task 1 encompassed the economic valuation of personalised pricing/offers.

Main Task 2 – Consumer survey carried out in all twenty-eight EU Member States, plus Iceland and Norway, to assess consumers' awareness, opinions, concerns and problems experienced vis-a-vis targeted adverts, personalised ranking of offers and personalised pricing.

Main Task 4 – Mystery shopping exercise (in 8 Member States) attempting to replicate consumers' "real life" experiences, when searching online for a series of goods/services in e-commerce websites, in order to assess the prevalence of personalised ranking of offers (changing the order of search results to highlight specific products) and personalised pricing (customising prices for some users) practices. The mystery shopping exercise also assessed the level of transparency with which personalised pricing/offers are communicated to consumers.

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⁷ http://ec.europa.eu/newsroom/just/item-detail.cfm?item_id=59332

Main Task 5 - Behavioural experiments aimed at assessing consumers' ability to detect personalised practices. The experiments (that took place in the same 8 Member States as in the Mystery shopping) also explored the effect transparency and the way consumers' data is processed and communicated to them has on consumers' decision-making and their willingness to proceed with a purchase.

1.2. Main tasks and methodologies used

The five different research activities undertaken during the course of the study are discussed in turn in the following sections. More technical details of the research methods used in the study can be found in Annex 1.

1.2.1. Main task 1: Legal review and stakeholder consultation

The main **objectives** of the legal review and stakeholder consultation part of Task 1 were the following:

- Assessment of the EU Regulatory framework on online market practices applicable to personalisation;
- Identification of the practices related to personalised pricing/offers used by online firms, the type of personal data collected and how it is used and the overall problems that consumers experience (e.g. transparency issues, data protection issues, unawareness of how the data is collected and used etc.); and
- Assessment of the extent to which online sellers are aware and comply with national and EU legislation.

Task 1 encompassed the following sub-tasks:

Table 1: Legal review and stakeholder consultation - Sub-tasks performed

Sub-task	Objectives			
Legal review and desk research	 Provide an overview of the EU legal framework and related initiatives in relation to the online environment and their possible relevance to personalisation practices; Provide insights into the online market practices used by business operators to personalise offers and prices for consumers, based on desk research and review of relevant literature 			
Stakeholder consultation	 Design and deploy surveys to Consumer Protection Authorities and Consumer Organisations, Data Protection Authorities and National Experts in order to: collect detailed insights on the occurrence of personalised pricing/offers practices by online business operators related to the online market and their impact on the overall market functioning assess online sellers' compliance with the existing EU and national legislation in the area of online personalisation practices and data protection/consumer protection; and collect feedback on areas where further possible legislation may be required in relation to online personalisation practices, based on consumer concerns and problems identified. 			

Sub-task	Objectives
Business Operators surveys	 Design and deploy surveys to business operators active as e-commerce websites and to business operators active as technology companies involved in the development of personalisation practices in order to: assess the compliance of business operators with the existing EU and national legislation related to consumer protection and data protection, stemming from personalisation practices in online markets (where applicable); identify the means of collecting users' personal data and the mechanisms behind the algorithms used to build up consumer profiles, as well as the sensitivity of the data collected from individuals; assess the challenges and barriers faced by business operators when engaging in personalised pricing/offers practices or when trying to ensure compliance with the existing EU and national regulatory framework; identify the differences in online personalisation techniques by country/region, by market sector or by company size; and determine the factors that drive online firms to employ personalised pricing/offers and the way the use of these practices is communicated to consumers; provide assessment on whether there is more discrimination in markets where competition is stronger or whether there is less

The **stakeholder consultation** consisted of dedicated surveys addressed to:

- Consumer Protection authorities (CPAs);
- Data Protection authorities (DPAs);
- Consumer Organisations;
- National Experts; and
- Business operators.

It relied chiefly on online questionnaires that were distributed to the stakeholder groups across each of the 30 countries covered by the study. The fieldwork took place between May and October 2017⁸. Additional data collection methods, such as interviews, were deployed to gather further insights on the topics from relevant experts. For a detailed description of the methodology used for the stakeholder surveys, please refer to Annex 1. All figures for the stakeholder consultations (other than those mentioned directly in the main body of the Report) have been included in Annex 3.

1.2.2. Main task 1: Economic valuation

The objectives of the economic valuation were as follows:

- "Assess the economic value of personalised pricing/offers via, inter alia, economic modelling, and
- To investigate how this value is divided between sellers and consumers (both those directly involved, and in the broader economy)";

⁸ Except for the business operators' survey, which continued up until November 2017 and the questionnaire addressed to consumer organisations that took place in the same month.

In order to meet these objectives, the economic valuation needed to assess whether personalisation has an impact on:

- Products shown to consumers;
- Prices paid by consumers, either because they pay different prices for the same product, or because they are shown different products;
- Consumer welfare and consumer demand.

The economic valuation also included a qualitative exploration of the expected welfare impacts of personalised pricing/offers.

The economic valuation used data from a number of sources to conduct its analysis. The sources are summarised in the table below. A more detailed methodology is provided in the Annex.

Table 2: Data sources for the economic effects of personalisation

Output	Collected in which task	Data collected relevant to assessing economic effects of personalisation
Quantitative estimate of the allocation of surplus between consumers and sellers via the impact of personalised pricing on profits	Task 4 (Mystery Shopping)	Data is collected on prices when: -Sellers can observe consumer characteristics e.g. online history, operating system and browser; -Sellers cannot observe consumer characteristics
Quantitative estimate of the existence and extent of personalised ranking of offers	Task 4 (Mystery Shopping)	Data is collected on top-ranked products when: -Sellers can observe consumer characteristics; -Sellers cannot observe consumer characteristics CROSSED WITH -Whether shoppers indicate that they typically search for 'high-end' or 'discount' products for specific product categories e.g. whether top-ranked products for TVs are different for 'high-end' TV shoppers compared to 'discount' TV shoppers
Qualitative exploration of the impact of personalised ranking of offers on consumer welfare, via the impact of reduced search costs/better matches to the consumer demand (measured by the probability of purchase)	Task 5 (Behavioural Experiment)	Data is collected on whether and/or how: -Consumers notice online personalisation -Consumers respond to online personalisation (e.g. by switching platforms, clearing cookies or proceeding to a purchase) -Benefits or concerns with personalisation are linked to drivers of consumers' purchase/browsing decisions

Output	Collected in which task	Data collected relevant to assessing economic effects of personalisation
Qualitative exploration of the impact of personalised pricing/offers on consumer welfare	Task 2 (Consumer Survey)	Data is collected on whether and/or how: -Consumers notice online personalisation; -Consumers respond to online personalisation (e.g. by following product recommendations if relevant, or by taking steps to 'anonymise' their searches) -Consumers perceive that online personalisation has an impact on the range of products for which they shop, or which they purchase -Consumers perceive benefits or concerns with online personalisation -The benefits and concerns are linked to drivers of consumers' purchase decisions
Qualitative assessment of personalised pricing impacts on welfare in selected markets	Task 1 (stakeholder consultation)	Data is collected on: -On what parameters are consumer profiles for personalising prices and offers based? (e.g. history of clicks/purchases, visits to price comparison websites etc.) -Value of targeted advertising

Source: LE Europe

1.2.3. Main task 2: Consumer survey

The objectives of the consumer survey were to provide a better understanding of consumers':

- awareness/knowledge of personalised practices;
- perceived incidence of personalised practices;
- perceived benefits of personalised practices;
- concerns with respect to personalised practices;
- experiences with personalised practices and complaints;
- overall opinions on personalised practices; and
- cookie knowledge and usage, and how this impacts their online behaviour.

Special attention was paid to the comparison between the three main personalisation practices covered by this study:

- *online targeted advertising* (via banner adverts, pop-ups, etc., targeted based on data on consumers' online behaviour);
- *online personalised ranking of offers* (different consumers seeing different search results when searching for the same product online); and
- *online personalised pricing* (different consumers seeing a different price for the same product online).

The consumer survey covered the 28 EU Member States (EU28), as well as Norway and Iceland. The survey was conducted online in all countries where online penetration was sufficient to ensure the required number of interviews and quality of the sample. This applied to 29 of the 30 countries covered; in Cyprus, the survey was conducted using Computer Aided Telephone Interviewing (CATI).

Fieldwork took place between 27 June and 19 July 2017⁹. In total 23,050 respondents completed the survey: 21,734 in the EU28, 513 in Iceland and 803 in Norway.

For a more detailed overview of the methodology and the complete version of the questionnaire for the consumer survey, please refer to Annex A1.4 and Annex A1.5. Annex 4 includes the tables with all results for Task 2, split out by country and a series of sociodemographic characteristics.

1.2.4. Main task 4: Mystery shopping exercise

Below a brief outline of the methodology for the mystery shopping is provided. Please refer to Annex A1.6 for detailed information on the methodology. The evaluation sheet used by the mystery shoppers can be found in Annex A1.7.

The mystery shopping exercise had as objective to replicate consumers' 'real life' experiences when searching for a series of goods/services on e-commerce websites. The aim was to assess the prevalence of personalised ranking of offers (changing the order of search results to highlight specific products) and personalised pricing (customising prices for some users) practices on e-commerce websites in the EU and detect their magnitude. This was based on a number of different parameters like means of entry to the e-commerce website, use of browser, use of device etc. The data from the mystery shopping exercise fed directly into the economic valuation described above.

⁹ Except in Iceland, where fieldwork was completed on 31 July.

The mystery shopping was conducted in eight EU countries: Czech Republic, France, Germany, Poland, Romania, Spain, Sweden and the UK¹⁰. Four of the six goods/services categories proposed in the ToRs were included in the mystery shopping exercise: 1) TVs; 2) shoes; 3); hotels; and 4) airline tickets (not websites of airlines as such but instead those of platforms that sell air tickets)¹¹.

The mystery shopping exercise encompassed 4 scenarios and was executed in a random order (ABCD, BCAD, CABD), by one shopper each time in one continuous shop for one of the four types of products mentioned above. Each scenario contained between 2-4 steps in which shoppers performed several pre-described actions before noting down the products and prices observed.

Table 3: Summary of scenarios for the Mystery Shopping exercise

Table 3: Summary of scenarios for the Mystery Snopping exercise		
Scenario	Key characteristics/aims	
Scenario A - Search engine	 Shoppers entered the same search query on their indicated preferred search engine (e.g. Google) or DuckDuckGo (a search engine that does not track the user) to surf to the same predefined destination e-commerce website. 	
	 To test whether the search engine used is a parameter for personalised pricing and offers. 	
	 To look at possible differences between a search engine with and without a search history. 	
	 Carried out on a desktop/laptop. 	
Scenario B - Price comparison website	 Shoppers accessed the same e-commerce website via 1) a predefined comparison tool website and 2) directly, by entering the URL. 	
	 To look at whether the use of a price comparison tool is a parameter for personalisation. 	
	 Carried out on a desktop/laptop. 	
Scenario C - Browser	 Shoppers consecutively used their indicated preferred browser and another (less used or freshly installed) browser to access the same e- commerce website. 	
	 To test if the browser is a parameter for personalisation. 	
	 To look at possible differences between a browser with and without search history. 	
	 Carried out on a desktop/laptop. 	
Scenario D - Mobile device	 Designed to test whether shoppers observe different offers/prices when using their mobile 	

¹⁰ The selection of countries was based on geographic coverage, year of entry to the EU, internet penetration and

retailers/manufacturers, office supplies/electronics, department stores, hotel and travel agencies, etc. Hannak et al. could not find evidence for personalisation on car rental websites. They also note that car rental websites tend to order cars by type, which precludes to a large extent personalised ranking of offers. For this

reasons, car rentals were excluded from the mystery shopping.

prevalence of online shopping, the proportion of enterprises selling online and consumers' views on privacy and security.

11 The selection was made based on evidence from the literature on where personalisation is particularly likely to take place. Hannak et al. found evidence for price discrimination and steering on general online e-commerce websites and travel/hotel websites. Mikians et al. (2013) list the retailers with the largest number of instances of price variations in their study. The list includes a diverse set of websites that include clothing

Scenario	Key characteristics/aims
	device, compared to all other scenarios that utilised a desktop/laptop.
	 Contained a step in which shoppers searched for the price of an existing pre-defined product, to facilitate the detection of personalised pricing.

All scenarios made use of shoppers' 'real life' online profiles; hence, all shoppers answered extensive questions about their online behaviour on both their desktop/laptop and mobile device¹².

Control steps and control shops were included in the mystery shopping to be able to identify inconsistencies that cannot be explained by the parameter(s) for personalisation tested:

- Control step: All four scenarios included a step (the "control step") in which the shoppers recorded the products and prices on the specified website of the shop using the incognito/privacy mode of the browser. This simulated deleting cookies without influencing shoppers' cookie based consumer profile for subsequent steps¹³.
- Control shop: The usage of the incognito/privacy mode of the browser (or deleting cookies) does not protect against more advanced forms of online tracking (see also Section 3.1.2). Hence, as part of every block of shopping exercises to the same website, a researcher from the subcontractor carried out a simultaneous independent 'control shop' using an 'anonymised' browser ¹⁴. Tests showed that this achieved de-personalisation/ prevented against more advanced forms of online tracking, meaning that websites could not infer unique identifiers and/or personal characteristics from the browser/computer setup used by the researcher¹⁵.

To account for the crucial factor of timing, the mystery shopping exercise was carried out in 3-hour time-brackets. A single shop was accompanied by a control shop carried out in the same time bracket.

In total, across the eight countries and four products, a total of 717¹⁶ evaluations (i.e. shops) were completed between 1 June and 25 August 2017 on a total of 160 EU websites by 254 mystery shoppers.

1.2.5. Main task 5: Behavioural experiment

The behavioural experiment and corresponding post-experiment questions were completed online by 6,580 participants across the UK, Germany, France, Spain, Sweden, Czech Republic, Poland and Romania (the same countries as in the mystery shopping).

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¹² For the profile of the shoppers and for information about how shoppers were selected, see Annex A1.6.10.

¹³ In the incognito/privacy modes of the most frequently used browsers, cookies from previous sessions are not used, and neither is other persistent data generated in previous browser sessions, such as the cache, other local storage, etc. See: Meng Xu et al., 'UCognito: Private Browsing without Tears', School of Computer Science, Georgia Institute of Technology (2015). Link: http://wenke.gtisc.gatech.edu/papers/ucognito.pdf

The following measures were taken to achieve de-personalisation in the independent control shops: 1) shops were carried out over a VPN network that protects personal identity and location, using an IP address for the country of the shop to prevent "geo-blocking"; 2) the browser (Firefox or Chrome) was de-installed (if already installed) and subsequently re-installed, with no plugins installed 3) the 'Ghostery' browser extension/plugin was installed to block all JavaScript "tags" and "trackers" as well as more sophisticated forms of tracking such as canvas fingerprinting; and 4) prior to the shop all cookies were deleted and the incognito/privacy mode of the browser was turned on (with Ghostery allowed as the only active extension). See also Annex A1.6.4.

¹⁵ A test on the website Panopticlick.eff.org identified the browser configuration used for the independent control shop as "not unique", meaning that the browser did not leave a unique fingerprint that would make it possible to track a specific user. This contrary to the great majority (83% or more, depending on the sample) of browser configurations tested at Panopticlick, which did leave a unique fingerprint. See also Annex A1.6.4.

¹⁶ Excluding control shops.

The objectives of the behavioural experiment were to:

- Assess "consumers' ability to detect personalised pricing/offers";
- Test consumers' "willingness to proceed to purchasing online if there was more transparency to the way their own personal data is processed and communicated"; and
- Determine how the layout, format and content of 'information' influences their decisions.

The behavioural experiment used the online environment of a simulated price comparison website for each of three products (car rentals, TVs and holiday accommodation). The experiment tested:

- Whether consumers realised personalisation practices were occurring within the experiment, and their understanding of these practices.
- Actions taken participants purchasing products or taking steps to counter personalisation by switching platforms or clearing cookies; and
- Participants' feelings regarding personalisation.

The experiment varied the type of personalisation (called scenarios in the behavioural experiment):

- The 'baseline' or 'no personalisation' scenario, where search results were presented randomly;
- Personalised ranking of offers where participants were shown different products based on either their browser or previous search history;
- Price discrimination where participants were shown either higher, or lower, prices for the same product depending on their previous search history; and
- Targeted advertising where participants were shown a targeted advertisement, combined with either random sorting of search results, or results sorted based on their previous search history.

The experiment also tested whether participants' comprehension, actions or feelings changed if personalisation was communicated to them more transparently. The variation of communication transparency were the experimental treatments.

- Low transparency: where it was not made clear to the participant that results were personalised;
- High transparency: where participants received salient communication that results were personalised to them; and
- High transparency + action: where participants received the most salient communication of personalisation, and it was easier for them to clear cookies and search again.

The following example (Figure 1) illustrates the difference between treatments, for a participant allocated to car rentals, where personalised ranking of offers is based on the participant's previous searches.

The text shown in red, or marked with a red box, illustrates the personalisation applied. This is shown here for illustrative purposes; the text was not shown in red in the experiment.

In the low transparency treatment, the participant was shown a price comparison website screen without being explicitly told that personalisation was occurring, and where the sorting criterion (search results are sorted by 'Recommended') was not salient/ was missing entirely.

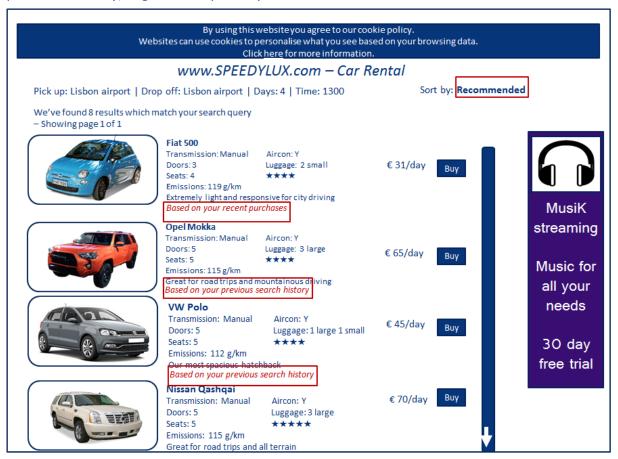
The behavioural experiment mock-ups in the report have been changed from the images shown to respondents, for copyright reasons. All images relating to the behavioural experiment in the report have been obtained using Creative Commons licenses and are free of copyright restrictions.

Figure 1 : Product selection screen: Personalised Ranking of Offers scenario (based on previous search), Low transparency



In the high transparency and high transparency plus action treatments, the participant was shown a price comparison website with explicit information that results were personalised based on their previous search. In addition, it was made salient to participants that search results were sorted by 'Recommended'.

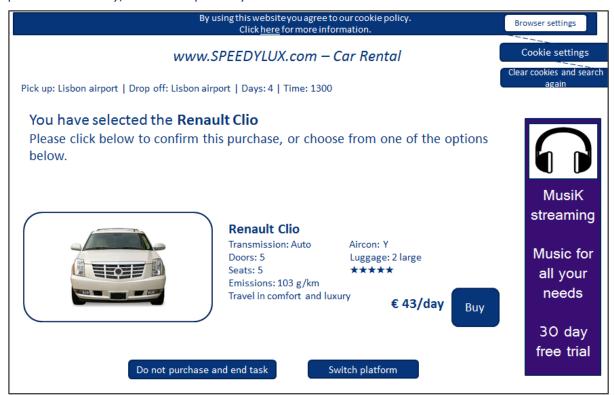
Figure 2: Product selection screen: Personalised Ranking of Offers scenario (based on previous search), Higher transparency treatments



After participants made their choice, they were asked to confirm their selection, or alternatively to switch platforms or clear cookies.

In the low transparency treatment, the 'clear cookies' button was towards the top of the screen and participants had to go through a three-step process to clear cookies and search again. This procedure mimicked the effort that consumers must go through to prevent personalisation practices. In addition, participants were not informed that they experienced personalisation.

Figure 3: Product selection screen: Personalised Ranking of Offers scenario (based on previous search), Low transparency treatment



In the high transparency treatment, participants were informed about personalisation, but still had to perform three clicks to clear cookies, and the 'clear cookies' button was still placed towards the top of the screen in the same less obvious place.

Figure 4: Product selection screen: Personalised Ranking of Offers scenario (based on previous search), High transparency treatment



In the high transparency + action treatment, participants were informed about personalisation, the 'clear cookies' button was placed in a more obvious position, and participants could now clear cookies with one click instead of three.

Figure 5: Product selection screen: Personalised Ranking of Offers scenario (based on previous search), High transparency + action treatment



A more detailed methodology is provided in Annex A1.8.

1.3. Structure of the report

The report comprises of 8 chapters:

- 1. Background, introduction and research objectives of the study
- 2. Online personalisation practices: an introduction
- 3. Online sellers: Type of personal data collected, transparency in communication and compliance with relevant EU and national legislation
- 4. Consumers' awareness and perception of personalised pricing/offers and problems reported
- 5. Research on the incidence and magnitude of online personalised pricing/offers
- 6. Influence of personalised pricing/offers on consumers' decisions and remedies
- 7. Economic effects of online personalisation on consumers and sellers
- 8. Conclusions and policy approaches

Chapter 2 provides a concise introduction to the three main personalisation practices covered by this study: targeted adverts, personalised ranking of offers and personalised pricing, based on findings from the literature review. Chapter 3 focusses on the online sellers' perspective: what type of personal data do online sellers collect and how? Do they communicate this to internet users and are sellers using online personalisation techniques in compliance with relevant EU and national legislation (insofar as this can be determined, considering the limited evidence).

Chapter 4 takes a look at the consumer angle. This chapter is chiefly based on the consumer survey supported by additional findings from the stakeholder survey and the behavioural experiment. The chapter looks inter alia whether consumers are aware of any kind of online personalisation, are able to identify online personalisation when it occurs, how they perceive this kind of personalisation, and if they experienced problems with either online targeted adverts, personalised ranking of offers and/or personalised pricing, and whether they reported about this and to whom.

Chapter 5, which is mainly based on findings from the mystery shopping, looks at whether empirical evidence was found for the existence of online personalised ranking of offers and personalised pricing. This mystery shopping exercise was constructed around a series of parameters, for which the limited literature available has hinted that they might be responsible for online personalisation, and covered 8 EU Member States, 4 sectors/products (airline tickets, hotels, shoes and TVs) and 160 websites. Chapter 6 switches back to the consumer point of view and looks at the evidence assembled through the behavioural experiment on the possible influence of personalised pricing/offers on, among others, consumers' online purchasing decisions. Chapter 7 explores the economic effects (e.g. on prices paid by consumers, consumer welfare and demand) of online personalised pricing and offers, insofar as data allows for this.

1.4. Terminology

In the table below a definition is provided of the key concepts/terminology used in this study.

Tarres	Definition
Term	Definition
Online personalisation	A practice that involves using data collected from an individual's online activity (including their webbrowsing behaviour) to deliver targeted content and adaptive web experiences. It is an umbrella term that encompasses also personalised pricing, personalised ranking of offers and online targeted advertising (see below).
Online personalised pricing	Personalised pricing uses data collected from an individual's online activity (including their webbrowsing behaviour) to customize prices for goods and services for users. Hence, online traders have the possibility to charge a different price to different people for the same goods or services online.
	"Personalised pricing is a relatively refined form of price discrimination where the firm observes some heterogeneity among consumers, and bases the price it charges on that heterogeneity." Price discrimination refers to a "well established business practice" when companies charge, "a different price to different people for the same good or service, for reasons not associated with costs" (UK Office of Fair Trading (2013)).
	The Guidance on the implementation/application of Directive 2005/29/EC on unfair commercial practices) talks about the possibility of tracking and profiling consumer behaviour [that] enables traders to personalise and target advertising and offers for

Taum	Definition
Term	Definition specific consumers" in the form of personalised pricing.
Online targeted advertising	A marketing practice that uses data collected from an individual's online activity (including their webbrowsing behaviour) to select advertisements to display (e.g. via pop ups, ad ("advert") space, banner ads ("adverts"), emails etc.) or other forms of commercial content for marketing purposes. It is an umbrella term for different types of online advertising that targets users, based on collected information of their online behaviour such as contextual, segmented, behavioural advertising etc. The difference between the types of targeted advertising is the data and information on the user that these practices are basing their advertising on.
	As opposed to contextual advertising that targets users, based on the content of the webpage they are visiting or the keyword typed in the search engine and to segmented advertising (based on characteristics which the user has provided for example upon registration on websites and which may contain personal data such as age, location etc.), online behavioural advertising (OBA) encompasses much more information of the individual users' online life over time and allows for more detailed profiling ¹⁷ .
	The current study focuses more on online behavioural advertising (see below). Nonetheless, it covers all these types of advertising, given the fact that different characteristics and behaviour patterns while surfing the web can be used to segment consumers.
Online behavioural advertising	"Advertising that is based on the observation of the behaviour of individuals over time. Behavioural advertising seeks to study the characteristics of this behaviour through their actions (repeated site visits, interactions, keywords, online content production, etc.) in order to develop a specific profile and thus provide data subjects with advertisements tailored to match their inferred interests" (Article 29 Working Party, <i>Opinion 2/2010 on online behavioural advertising</i>).
Targeted emails	A form of targeted advertising (see above) that companies use in order to "segment" and "target" users in a mailing list, based on different categories of

¹⁷ European Commission (2010). Article 29 Data Protection Working Party 00909/10/EN WP 171, "Opinion 2/2010 on online behavioural advertising". Available at: http://ec.europa.eu/justice/article-29/documentation/opinion-recommendation/files/2010/wp171_en.pdf

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Term	data collected, by means of sending advertisements for product offers to the users' personal email addresses. It can sometimes pose issues related to data privacy and can sometimes fall under the category of "spam" if they are persistent, unsolicited and, unduly, without prior permission by the receiver (e.g. "opt-in" list as opposed to "bulk list"). In principle consent (thus prior permission) is needed, unless there is an existing customer relationship (see Article 13 ePrivacy Directive)
Personalised ranking of offers	A practice that uses data collected from an individual's online activity (including their web-browsing behaviour) to change the order of search results to highlight specific goods and services, when consumers search for the same products online. Also referred to as "personalised offers" or 'price steering'.
Dynamic Pricing	The Guidance on the implementation/application of Directive 2005/29/EC on unfair commercial practices defines dynamic pricing as a practice that changes "the price for a product in a highly flexible and quick manner in response to market demands".
	According to the Guidance document, "Under the UCPD, traders can freely determine the prices they charge for their products as long as they adequately inform consumers about total costs and how they are calculated (Articles 6(1)(d) and 7(4)(c) UCPD). However [] a dynamic pricing practice where a trader raises the price for a product after a consumer has put it in his digital shopping cart could be considered a misleading action under Article 6(1)(d) UCPD"
	The OFT (2013) refers to dynamic pricing as a practice where "online retailers use fluctuations in demand to change the prices of their products depending on availability. Products which are likely to be priced dynamically are those which may be perishable, timesensitive (airline or travel tickets), those with a depreciating value (technology based goods), or if they are scarce (event tickets)."18

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¹⁸ OFT (2013), "Personalised Pricing: Increasing Transparency to Improve Trust", Report. Available at:http://webarchive.nationalarchives.gov.uk/20140402142426/http://www.oft.gov.uk/shared_oft/markets-work/personalised-pricing/oft1489.pdf.

2. Online personalisation practices: an introduction

The exponential growth of connected devices and the volume of information generated by users online (e.g. when they shop online for products, use of search engines, online platforms and social networks or fill in online questionnaires in order to register to websites) coupled with technological advances in data analytics and machine learning has enabled the emergence of new data-driven business models in the digital and advertising ecosystem. A report by IDC and Open Evidence on the European data economy anticipates the data market in the EU to reach 106.8 billion EUR by 2020 with an annual growth rate of 15.7% since 2016¹⁹.

More specifically, the retail industry was among the leading industries in 2016 by number of data user companies²⁰. Furthermore, this retail industry experiences significant benefits by adopting data-driven technologies such as increase in revenues (e.g. by attracting new customers or retaining existing ones; or gaining better understanding of their needs and thus, building better customer relationships) or cost optimisation by more refined interpretation of existing data²¹. Data-driven pricing and personalisation are also a key success factor for the travel sector²², especially airline tickets²³. On the other hand, the fact that online personalisation practices rely on the collection of large amounts of consumer data, including in some cases personal data, may raise consumers' concerns in relation to data privacy and transparency (explored in details in Chapter 3 and Chapter 4).

In this context, online traders have adopted practices that focus on improving their understanding of consumers' behaviour and needs by providing personalised tailored offers through the use of data. As a result of personalisation practices, businesses can maximise profits as companies are able to more accurately estimate the maximum price that consumers are willing to pay for a product, based on the data collected on them. Hence, companies would be in a position to offer cheaper products or services for consumers with lower willingness to pay who might have otherwise opted out and purchased similar products from a competitor, or attract them as potential customers. On the other hand, consumers thought to have higher willingness to pay, may be charged a higher price.

In the sections below, the three main online personalisation practices covered by this study are introduced, based on the available literature:

- Targeted advertising (Section 2.1);
- Personalised ranking of offers/(Section 2.2); and
- Personalised pricing (Section 2.3)

2.1. Features of online commerce that enable personalisation

The economic models that can help us to understand online personalisation draw from the literature on price discrimination. Price discrimination is when an online producer sells a similar (or identical) product to different consumers at different prices. A number of lessons

¹⁹ IDC, Open Evidence (2016), European Data Market: The Data market and the Data Economy, Second Interim report. Available at: http://datalandscape.eu/study-reports

²⁰ The EU Data Landscape, "How much are European companies using data?", Data-driven Stories News. Available at: http://datalandscape.eu/data-driven-stories-news/how-much-are-european-companies-using-data

²¹ IDC, Open Evidence (2017), European Data Market, Final report, p.148. Available at: http://datalandscape.eu/study-reports

McKinsey&Company. "Powered by data, driven by people: The travel sector's future". Available at: https://www.mckinsey.com/industries/travel-transport-and-logistics/our-insights/powered-by-data-driven-by-people-the-travel-sectors-future

²³ Sabre Airline Solutions. The evolution of customer data: how data-driven personalization will change the game for airlines. Available at: https://cdn2.hubspot.net/hubfs/447188/SS Files/CC Push 2/Customer Data WHITEPAPER.pdf

from the price discrimination literature also apply to offer personalisation and to targeted advertising.

First degree – also known as perfect – price discrimination means that a firm charges each customer the maximum price the customer is willing to pay. First degree price discrimination is rarely possible in real markets as the seller would need to have perfect information about the consumer's product preferences. First degree price discrimination is instead used as a theoretical benchmark in models of price discrimination.

Third degree price discrimination, by contrast, relies on partitioning consumers based on characteristics that are more readily observable.²⁴ A firm using this pricing strategy sets a different price for different groups of consumers (e.g. student discounts, geographical pricing). The pricing decision is based on known group characteristics (e.g. students tend to be more price sensitive) rather than individual characteristics.

The distinction between first and third degree price personalisation is equally applicable to offer personalisation and targeted advertising, as these personalisation techniques depend in the same way on the firm's information about the characteristics of their customers.

E-commerce increasingly enables firms to move from third degree price discrimination towards first degree price discrimination. Similarly, firms are able to individually target offers and advertisements. Two characteristics of online retail contribute to this development.

- Firstly, e-commerce websites have access to a greater range of consumer characteristics that they can use to segment their consumers, compared to brickand-mortar shops. The OECD (2016) identifies the increasing availability and affordability of "big data" as the key factor underlying the new potential for more targeted differential pricing.²⁵ The firms' analysis of such data can identify many group characteristics that correlate with a consumer's willingness to pay, leading for example to Android users experiencing different prices from Windows users²⁶ or shoppers in the US paying more than customers in Canada for the same product on the same website.²⁷ But effective use of big data allows pricing, ranking of offers, and advertising that is even more individually targeted. The shopper's search history, browsing history, purchasing history, and other information available to online retailers through cookies and other tracking tools can allow the retailer to estimate the preferences and budget constraints of individual consumers (rather than groups) with increasing accuracy, including their willingness to pay for various products. This finding is in line with the stakeholders' survey conducted for this study: business operators advocated that the costs of collection and analytics of customer information has decreased substantially with technological progress and the emergence of specialised firms that can be hired for the task.
- Second, e-commerce technology makes it easier to display different prices, products, and adverts to different consumers.

2.2. Targeted advertising

Online advertising is a large and growing market. According to an estimate by the media agency Zenith (2017), digital advertising now accounts for over a third of global media advert spending and most of the sector's growth.²⁸ The research company eMarketer

²⁴ Second degree price discrimination is related to quantity discounts and as such does not rely on information the seller knows about costumers.

²⁵ OECD (2016). "Price Discrimination: Background Note by the Secretariat." Available <u>here</u>.

²⁶ IB Times (2014), Mac and Android Users Charged More on Shopping Sites Than iPhone and Windows Users

²⁷ CBC News (2017), How companies use personal data to charge different people different prices for the same product

²⁸ Zenith (2017). "Advertising Expenditure Forecasts June 2017". Available at https://www.zenithmedia.com/wp-content/uploads/2017/03/Adspend-forecasts-June-2017-executive-summary.pdf

predicts that in 2017, global spending on digital advertising will exceed USD 228 billion (EUR 202 billion²⁹). This global digital advertisement market is largely dominated by the Google and Facebook "duopoly" – both companies combined account for 63.1% out of the total online advertisement market in 2017; a market share that is expected to grow further³⁰. With 22% of the total digital advertisement spending in the US in 2017, the retail sector was the biggest digital advert spender – a trend that is expected to continue through 2020^{31,32}.

In Europe, digital advertising generates EUR 41.9 billion annually, growing at the rate of 12.3% in 2016, according to a report by IHS Markit (2017)³³. Three European countries – the United Kingdom, Germany and France – were among the top 10 major online advertising markets globally in 2017 in revenue, with 11.72, 7.37 and 5.13 billion dollars spent on online adverts, respectively³⁴.

In this context of a rapidly expanding online advertising market, targeted advertising is among the general public the most well-known online personalised practice covered by this study (see Chapter 4). In the current study, with targeted advertising/adverts, we refer to the following three main business operators' strategies:

- **Behavioural advertising** is understood as "advertising that is based on the observation of the behaviour of individuals over time. Behavioural advertising seeks to study the characteristics of this behaviour through their actions (repeated site visits, interactions, keywords, online content production, etc.) in order to develop a specific profile and thus provide data subjects with advertisements tailored to match their inferred interests" ³⁵;
- **Contextual advertising** is defined as "advertising that is selected based on the content currently being viewed by the data subject. In the case of a search engine, content may be derived from the search keywords, the previous search query or the user's IP address if it indicates their likely geographical location"³⁶; and
- **Segmented advertising** refers to "advertising selected based on known characteristics of the data subject (age, sex, location, etc.), which the data subject has provided at the sign up or registration stage". ³⁷

Prevalence of targeted advertising on the online advertising market

An increasing share of global digital advertising spending and growth is attributable to the use of data, and targeted targeting in particular. In a 2016 Eurostat survey of EU businesses, 25% of all enterprises employing at least 10 people reported using internet

²⁹ Using average ECB reference exchange rate for 2017.

³⁰ eMarketer (2017). Available at https://www.emarketer.com/Article/Google-Facebook-Tighten-Grip-on-US-Digital-Ad-Market/1016494

³¹ Smart Insights. 2016 US Digital Marketing Budgets: Statistics and Tools. 25 November 2016. Available at: https://www.smartinsights.com/internet-marketing-statistics/2016-us-digital-ad-spend-statistics-trends/

The Wall Street Journal (WSJ), Retail Marketers to lead digital ad spending through 2020. Available at: https://www.wsj.com/articles/retail-marketers-to-lead-digital-ad-spending-through-2020-1462983786
 IHS Markit (2017). The Economic Value of Behavioural Targeting in Digital Advertising. Available here.

³⁴ Statista, "Online advertising revenue in major online advertising markets in 2017 (in billion U.S. dollars): https://www.statista.com/statistics/246570/largest-online-advertising-markets/

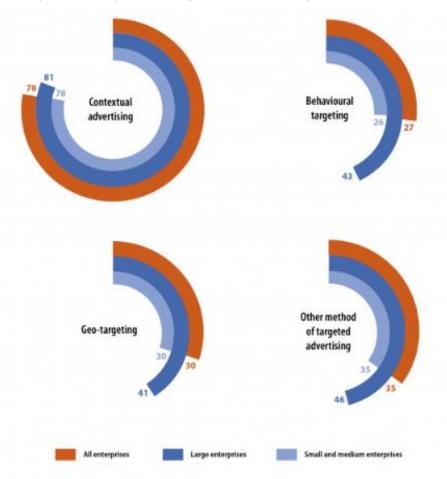
³⁵ Please see Opinion 2/2010 p. 4, referenced above¹⁷

³⁶ Opinion 2/2010 p.5¹⁷

³⁷ Opinion 2/2010 p.5¹⁷

advertising.³⁸ Of these, 78% have adopted contextual advertising (see Figure 6)³⁹. Eurostat data further shows that 27% of all enterprises using internet adverts make use of behavioural advertising; this share is particularly high for large companies (43% use behavioural advertising) and to a lesser extent for SMEs (26% use behavioural advertising). Other methods of targeted advertising (e.g. "static" internet adverts on subject-specific websites or online newspapers, magazines and blogs) were used by 35% of all enterprises using internet adverts, according to Eurostat. As with behavioural advertising, large enterprises employed these advertising techniques more frequently than SMEs (46% vs. 35%, respectively). According to Eurostat, "geo-targeting can be used in combination with contextual or behavioural targeting in order to further identify the needs of a potential customer"⁴⁰. Geo-targeting was used by 30% of all companies using internet adverts, with 41% of large companies and 30% SMEs using this method of targeted advertising.

Figure 6: Use of Internet adverts by type and by enterprise size, based on Eurostat data in the EU28 (% of enterprises using internet adverts)



Source: Eurostat, Use of Internet Ads by type and by enterprise size41

³⁸ The share varied between Member States from 46% in Malta, 42% in Sweden and 40% in Denmark at the high end of the spectrum to Bulgaria and Hungary (both 19%), France and Italy (18%), Portugal (15%) and Romania (12%) at the low end.

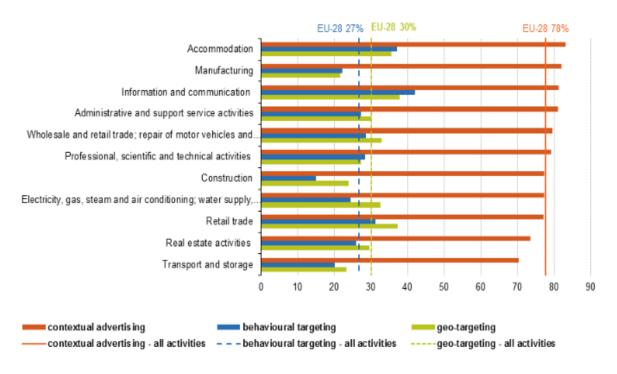
Eurostat, Internet advertising of businesses – statistics on usage of ads: http://ec.europa.eu/eurostat/statistics-explained/index.php/Internet advertising of businesses - statistics on usage of ads

⁴⁰ Eurostat referenced above³⁹

Eurostat, Internet advertising of businesses – statistics on usage of ads: http://ec.europa.eu/eurostat/statistics-explained/index.php/Internet advertising of businesses statistics on usage of ads

When looking at the Eurostat data on the use of internet adverts by type and by enterprise economic activity, shown in the table below, it can be noted that in all sectors 70% or more of the enterprises that use online adverts use contextual advertising. The "accommodation services sector" most frequently uses contextual advertising; over 80% of companies using online adverts in this sector use contextual advertising⁴². In the retail sector close to 78% use this form of advertising. It can be noted as well that approximately 35% of companies who use online advertising in the accommodation services sector and 30% of retailers use "behavioural advertising".

Figure 7: Use of internet adverts by type and by enterprises' economic activity, based on Eurostat data (% of enterprises using online advertising):



Source: Eurostat, Use of Internet Ads by type and by enterprise size⁴³

A study by IHS Markit⁴⁴ found that behavioural targeting is unevenly distributed across the European markets. The use of behavioural data is most prevalent in countries with high per capita advert spending, such as the UK, Netherlands and France. In these markets, behavioural targeting amounts to more than 50% of total online advert spending. In contrast, behavioural targeting in Southern and Eastern Europe accounts for a substantially lower (between 5% and 20%), albeit growing, share of total spending on online adverts. However, the econometric modelling employed in the study suggests that this discrepancy is likely to disappear over the next five years, as the share climbs to 70% in most European markets⁴⁵.

Carrascosa et al. (2015)⁴⁶ try to estimate the extent of targeted advertising by simulating online personas with different interests and observing advertisements displayed to the bots as they search and browse the web. They find that 10-94% of online advertisements are targeted, depending on the simulated area of interest. The study also compares the extent of behavioural advertising in the US and Spain, but finds no evidence of significant

⁴² Eurostat Internet advertising data referenced above⁴¹

of businesses Eurostat, Internet advertising statistics usage ads: http://ec.europa.eu/eurostat/statistics-explained/index.php/Internet_advertising_of_businesses_-_statistics_on_usage_of_ads

⁴⁴ IHS Markit (2017)33

⁴⁵ IHS Markit (2017)³³

⁴⁶ Carrascoca, Mikians, Cuevas, Erramilli and Laoutaris. "I always feel like somebody's watching me: Measuring Online Behavioural Advertising". Available at: https://arxiv.org/pdf/1411.5281v2.pdf

geographical differences. They find that the amount of targeted advertising a given persona receives depends on its economic value in the online advertising market. This value is estimated using Google Adwords' suggested CPC (cost per click) for keywords related to the persona (e.g. air travel, motor sports, movies etc.). More "valuable" personas (i.e. with more expensive keywords) are targeted more. This finding is in line with Papadopoulos et al. (2017), who study the distribution of prices paid for targeted advertising. They find that while advertisers pay a relatively low amount for an advert to be shown to an average user, there is a small portion of approximately 2% outlier users who cost 10-100 times more⁴⁷.

Different sectors also pay considerably different premia for targeted online advertising. For example, analysing data of their clients, the online advertising firm WordStream publishes industry benchmarks for advertising costs in Google Adwords (Google's advertising system in which advertisers bid on certain keywords in order for their clickable ads to appear in Google's search results and/or on other websites across the internet that use Google's advertising services) in the US. Table 4 shows the results. While in the categories "Dating & Personals" and "e-commerce" advertisers pay only \$0.19 and \$0.88 to Google for a click respectively, this figure is \$5.88 in "legal" services, \$4.20 in "employment services" and \$3.72 in "finance & insurance". However, according to the firm, the US market is the most expensive one in the world and the prices are considerably lower in many EU Member States. In EU countries, WordStream estimates that the prices range from 2% cheaper than the US in Austria to 92% lower in Slovenia⁴⁸. The average among the new Member States (EU13) is 79% lower than the US. Among the EU15, it's 41% less than the US⁴⁹.

One reason for the differences between industry sectors may be because, according to WordStream, certain business areas have a "very high lifetime customer value"⁵⁰ e.g. legal services, insurance or mortgage applications.

Table 4: Industry benchmarks for advertising indicators in Google Adwords search network

Industry	CTR (Click Through Rate) ⁴⁸	Average CPC (cost per click)	Conversion rate (CVR) ⁴⁸	Cost per Action (CPA) ⁴⁸
All	1.91%	\$2.32	2.70%	\$59.18
Advocacy	1.72%	\$1.72	4.61%	\$37.31
Auto	2.14%	\$1.43	2.27%	\$63.00
B2B	2.55%	\$1.64	2.58%	\$63.57
Consumer Services	2.40%	\$3.77	5.00%	\$75.40
Dating & Personals	3.40%	\$0.19	2.75%	\$6.91
E-Commerce	1.66%	\$0.88	1.91%	\$46.07
Education	2.20%	\$1.74	4.13%	\$42.13
Employment Services	2.13%	\$4.20	3.97%	\$105.79
Finance & Insurance	2.65%	\$3.72	7.19%	\$51.74
Health & Medical	1.79%	\$3.17	2.51%	\$126.29

Panagiotis Papadopoulos, Nicolas Kourtellis, Pablo Rodriguez Rodriguez, Nikolaos Laoutaris (2017). If you're not paying for it, you are the product. Available at: https://dl.acm.org/citation.cfm?doid=3131365.3131397
Paragraph Adwords WordStroam reports for a result of the product of the product

⁴⁸ For Google Adwords, WordStream reports for a range of sectors the average click through rate (showing how many people who view an online advert displayed by Google click on it), the average costs per click (the average price advertisers pay to Google for a click on an advert), the conversion rate (the proportion of clicks that lead to users performing an action defined by the advertiser, such as a sale), and the costs per action (the average costs for an advertiser for realising the specified action, such as a sale). See WordStream (2017). Average Cost per Click by Country: Where in the World Are the Highest CPCs?. Available here.

⁴⁹ The data don't include Cyprus, Estonia, Luxembourg, Malta, and the Czech Republic.

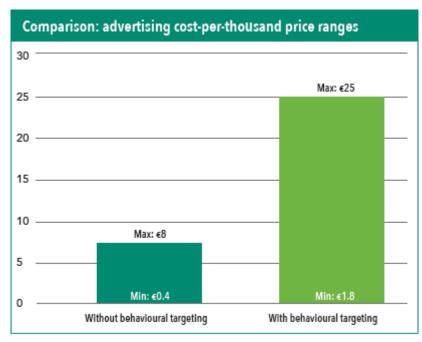
⁵⁰ WordStream (2017), How Does Google Make Money? The Most Expensive Keywords in AdWords

Industry	CTR (Click Through Rate) ⁴⁸	Average CPC (cost per click)	Conversion rate (CVR) ⁴⁸	Cost per Action (CPA) ⁴⁸
Home Goods	1.80%	\$3.19	3.68%	\$86.68
Industrial Services	1.40%	\$2.00	2.58%	\$77.52
Legal	1.35%	\$5.88	4.35%	\$135.17
Real Estate	2.03%	\$1.81	4.40%	\$41.14
Technology	2.38%	\$1.78	2.55%	\$69.80
Travel & Hospitality	2.18%	\$1.55	2.57%	\$60.31

Source: Analysis of client data by online advertising firm WordStream

There is also evidence that behavioural targeting has a positive impact on the revenues for media companies, as they charge higher prices for behavioural adverts. The impact is presented in the figure below (expressed as "cost per thousand", a measurement of how much it costs companies to reach 1,000 viewers)⁵¹.

Figure 8: Cost-per-thousand price ranges comparison for behavioural and non-behavioural targeting



Source: Average between five publishers in the EU-28 from IHS Markit industry survey, 2017. Data refers to banner advertising cost-per-thousand (CPM) that the publisher can charge to advertisers. CPM stands for the price to reach 1000 (mille) advertising impressions.

Source: HIS Markit (2017), The Economic value of behavioural targeting in digital advertising"

The market share of practices that enable targeted advertising, such as programmatic advertising and real-time bidding (RTB), has risen significantly over the past years and their importance is likely to continue to grow. Programmatic advertising refers to "advertising transactions that are based on automated platforms and that are driven by consumer data"⁵². RTB is a form of "real-time" programmatic advertising that allows

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⁵¹ IHS Markit (2017), The Economic value of behavioural targeting in digital advertising"

Magna Global, "New Programmatic Forecasts" 2015. Short summary available at: https://www.magnaglobal.com/wp-content/uploads/2015/10/MAGNA-GLOBAL-Programmatic-PR-Sept-2015.pdf

advertisers to bid for and target specific demographic groups based on consumers' personal and behavioural data⁵³ (see explanation of bidding on ad exchange platforms below in Figure 9). In 2017, the share of programmatic advertising (including RTB) as a percentage of the total digital advertising spending in the US was estimated at approximately 62% (RTB alone accounted for 42%)⁵⁴. In the US, the market share of programmatic advertising has experienced an increase of almost 10% since 2015 (when it accounted for 53% of the total digital advertising spending in the US)⁵⁵ and is expected to grow to approximately 65% by 2020 (when RTB's market is expected to have increased to 48%)⁵⁶.

The study by IHS Markit estimates that in Europe, 86% of programmatic advertising and 24% of non-programmatic advertising uses behavioural data. Behavioural data thus underpin €10.6 billion of the €16 billion digital display advertising market in Europe. Assuming unchanged regulatory conditions, the company estimates that this market would grow to €23.5 billion by 2020, with €21.4 billion informed by behavioural targeting⁵⁷.

Main actors in the online advertising market

The advertising ecosystem is highly complex and involves a variety of actors. A report by the Danish Data Protection Authority (Datatilsynet)⁵⁸ provided an overview of the key players in the online advertising industry, shown below.

Figure 9: Actors involved in the digital advertising

Buyers o	f ad space	Ad exchanges	Vendors of	ad space
Media Agencies Group M-gruppen (WPP) Red Media Consulting (IPG) Carat og Vizeum (Dentsu/Aegis) PH, OMD og Starcom (Omnicom) Trading desks Xaxis (WPP)	Demand Side Platform DoubleClick Bid Manager (Google) Flurry (Yahoo) BrightRoll (Yahoo) Xaxis MediaMath Turn The Trade Desk Rocktfuel DataXu	DoubleClick Adx (Google) Facebook Adx Microsoft Adx AppNexus (Microsoft) Right Media (Yahoo) OpenX AOL One Rubicon Video: AdapTV SpotXchange LiveRail (Facebook) Mobil:	Supply Side Platforms Schibsted Facebook Ex Admeld (Google) Rubicon Project Pubmatic Index Exchange Improve Digital Appnexus	Publishers Schibsted Dagbladet Polaris media Amedia Egemont Aller Startsiden Facebook Google
Accuen (Omnicom) Vivaki (IPG) Amnet (Dentsu/Aegis)	Appnexus	MODII: MoPub Smaato Flurry (Yahoo) BrightRoll (Yahoo)	Ad net Google Adsense Scandinavian AdNetwork Webtraffic (Schibsted) Amedia Marked	works
		Data and data analytics		
Data Management Cxence	Platforms	Data brokers	Market	research
Enreach Delta Projects Aggregate Knowledge, Adobe Lotame, Acxiom, Adchemy, D Digilant, Epsilon, Experian, Di Mediamath, Targetbase, Targ	atalogix, Demdex, Data gital, Lotame, Expe	om be Ilogix rian	TNS Gallup Norstat Nielsen Experian Comscore Kantar	

Source: Datatilsynet (2015), The Great data Race⁵⁹

⁵³ Smart Insights, "A Programmatic Marketing Glossary". 11 February 2016. Available at: https://www.smartinsights.com/internet-advertising/internet-advertising-targeting/programmatic-marketing-demystified/

⁵⁴ Statista, "Programmatic vs non-programmatic share of digital advertising spending in the United States from 2015 to 2020. Available at: https://www.statista.com/statistics/271499/forecast-for-the-market-volume-ofonline-advertising-in-the-us/

⁵⁵ Statista data referenced above⁵⁴

⁵⁶ Statista data referenced above⁵⁴

⁵⁷ IHS Markit (2017)³³

Datatilsynet, The Great Data race: How commercial utilisation of personal data challenges privacy. Report, November 2015: https://www.datatilsynet.no/globalassets/global/english/engelsk-kommersialisering-endelig.pdf

⁵⁹ Datatilsynet referenced above⁵⁸

The actors shown above serve the following functions in the ecosystem 60:

- Ad exchange platforms: Ad exchange platforms or marketplaces provide advert space for sale/purchase. These platforms historically emerged as platforms for RTB and programmatic buying of users. For example, as a first step, advertisers on the platform are notified each time a user is visiting specific websites and can perform a bid to display their advert. Advertisers are also given background information about the user's profile (e.g. age, gender, interests), provided by the ad exchange platform. This data can be used in combination with other data collected by the advertisers themselves (e.g. obtained through data brokers) to calculate their bid. The highest bidder wins and is allowed to place an advert on the page that the user is viewing. The whole process takes milliseconds⁶¹, as most of it is automated;
- Vendors of advert space include different companies selling advert space. Publishers include online newspaper websites, search engines or social media. They are capable of tracking consumers across websites and can obtain detailed personal information via user's login data. This data can be transmitted to advertisers, as it usually pertains to specific consumer groups. Publishers use supply-side platforms to sell advert spots. These supply-side platforms can also serve as ad exchange platforms. Ad networks, on the other hand, collect ad offerings from different publishers' websites and provide advertisers with selected groupings of ad "inventory";
- Buyers of advert space this includes advertisers and other market players who
 may assist them in placing their adverts such as media agencies. The latter usually
 have consumers' data due to their extensive customer base in the advertising
 industry, data which could be used for better targeted advertising. Demand-side
 platforms provide software which operates the adverts in real-time, based on predefined rules or algorithms agreed with the advertisers. This platform "purchases"
 users, based on data provided by the advertiser or obtained through cookies and
 social media. Trading desks are centralised platforms managed by media agencies
 on which companies can list their advertising space offering;
- Data analytics and market research companies their core business is based on collecting, analysing, sharing and transmitting of consumers' data to advertisers and other interested parties on the online market (please see Section 3.2 for more details on the practices of acquiring/transmitting/sharing of personal data on the data market and the role of data brokers, data analytics companies and data management platforms).

2.3. Personalised ranking of offers

Personalised ranking of offers, sometimes referred to as *personalised offers in the literature* (or also price steering), is a personalisation practice which relates to changing the order of search results to highlight specific goods and services, when consumers search for the same products online. Prices of the individual products do not change as such, but some online shoppers are nudged to first view and then purchase, for example, the high-value offers, as a result of companies re-ordering the search results based on a consumer's personal characteristics.

⁶⁰ Explanations elaborated based on the Datatilsynet report reference above⁵⁸

⁶¹ Datatilsynet referenced above⁵⁸

To this date there is relatively limited quantity of theoretical and empirical literature available about price steering in e-commerce. The media, or company reports, provide evidence in a scattered manner about individual practices, 62 but there is not a large literature systematically measuring online personalisation. This might be explained by the low awareness about the subject 63, as well as by the fact that online personalisation is a relatively new phenomenon linked to recent technological advances and growing importance of e-commerce. Another reason is that there are a number of technical obstacles to experimental measurements. Personalised ranking of offers based on individual attributes or user behaviour is hard to detect, as it is difficult to assess whether the differences in offers are due to personal characteristics or other contributing criteria 64. Nonetheless, some relevant literature is available, which is briefly discussed below.

Mikians et al. (2012) use bots with different simulated consumer characteristics to look for evidence of price steering on 200 websites (based in the EU and the US) spanning 35 product categories and 600 unique products. They looked at three distinct vectors that could be candidates for price steering: technological differences (operating system, browser, etc.), geographical location, and personal information. When they train the bots to appear to possess certain attributes (e.g. affluent versus budget conscious), **they find evidence of offer personalisation on several online hotels/tickets vendors.** They find no evidence of offer personalisation based on system preferences (OS/browser).⁶⁵

Hannak et al. (2014)⁶⁶ detect instances of offer personalisation by assessing 16 popular US e-commerce websites by comparing real-user data to a control shop. They also simulate controlled experiments using fake accounts, in which they find examples of personalisation based on the user's OS/browser, account on the site, and history of clicked/purchased products. However they note that most of the experimental shops did not reveal evidence of offer or price personalisation. **The evidence they find is limited and restricted to the hotel sector and in a few instances to general retailers**⁶⁷.

Another study by Hannak et al. (2015) provided evidence for location-based search personalisation (in Google Search) based on users' IP address. **However the study did not find evidence for these practices resulting in users being steered towards pricier products**⁶⁸.

⁶³ Aniko Hannak, "Personalization in online services: Measurement, Analysis and Implications". Dissertation presented to the College of Computer and Information Science. Northern University. 2016.

65 Mikians et al. (2012) 'Detecting price and search discrimination on the Internet' (2012). Link: http://conferences.sigcomm.org/hotnets/2012/papers/hotnets12-final94.pdf

https://www.ftc.gov/es/system/files/documents/public_comments/2015/09/00011-97593.pdf

⁶⁸ Kliman-Silver, Aniko Hannak, David Lazer, Christo Wilson, Alan Mislove. "Location, Location, Location: The Impact of Geolocation on Web Search Personalization" (October 2015). Available at: https://mislove.org/publications/Geolocation-IMC.pdf

⁶² For example, WSJ (2012), <u>On Orbitz, Mac Users Steered to Pricier Hotels</u>, CBC News (2017) <u>How companies use personal data to charge different people different prices for the same product</u>, WSJ (2012), <u>Websites Vary Prices</u>, <u>Deals Based on Users' Information</u>.

Wolfie Christl, Sarah Spiekermann. Networks of Control. Available at: http://crackedlabs.org/dl/Christl Spiekermann Networks Of Control.pdf

⁶⁶ Hannak, G. Soeller , D. Lazer, A. Mislov and C.Wilson, 'Measuring Price Discrimination and Steering on E-commerce Web Sites' (2014). Available at:

⁶⁷ Notably, on one travel website ("Cheaptickets/Orbitz") logged-in users received different offers for hotels. Specifically, on this website, on average out of 25 results per page ≈2 search results were new and ≈1 were moved to a different location for logged-in users, although for some travel destinations almost all results differed for users logged-in to their account. Another travel website ("Priceline.com") was shown to alter hotel search results based on the user's history of clicks and purchases. Users who previously clicked on or reserved low-price hotel rooms received slightly different overall results in a much different order, although this reordering was not correlated with prices. A third travel website ("Travelocity") altered hotel search results and the ordering of these results for users who browsed from iOS devices. This reordering of search results did not result in price steering, although evidence was found for price discrimination. On a home improvement website ("Home Depot") users on mobile browsers were steered towards different (on some days the study measured close to zero overlap between the results served to desktop and mobile browsers) and on average more expensive products.

Van Tien Hoang et al. $(2016)^{69}$ focussed specifically on how and if online consumer behaviour, such as visiting a website of luxury goods, clicking on expensive products, etc., affects the search results displayed to users (e.g. whether there is evidence of steering towards more expensive products). In line with the findings from Mikians et al. (2012), the research by Van Tien Hoang et al. found evidence of price steering based on user profiles (in this case on "Google Shopping", a price comparison website), as the search results of 'affluent users' were biased towards more expensive products.

2.4. Personalised pricing

Personalised pricing uses a wide range of data collected from an individual's web-browsing behaviour or information provided by the users themselves (e.g. by filling in online registration forms, usage of social networks, websites visited etc.) to customize prices for goods and services for some consumers. According to the UK's Office for Fair Trading, "personalised pricing is a relatively refined form of price discrimination where the firm observes some heterogeneity among consumers, and bases the price it charges on that heterogeneity.⁷⁰"

An OECD report (2016) on price discrimination⁷¹ argues that the digital economy and Big Data have had an important and transformative impact on companies' ability to employ personalised pricing⁷². However, the report noted that personalised pricing is not as widespread as online behavioural targeting (targeted adverts) and that companies are still in the stage of "experimenting with a number of strategies" by offering different prices to consumers to test their reactions and determine their willingness to pay⁷³.

Historically, the practice of personalised pricing in e-commerce first entered public spotlight in early 2000 when Amazon received big public criticism after being accused of charging lower prices to new buyers of DVDs and higher prices to its loyal DVD buyers (in the US), which was identified at the time by simply erasing one's cookies⁷⁴. The controversial nature of the practice (which may limit its use for sellers), as well as the fact that the technical possibilities for online personalisation have become much more advanced and hard to capture/measure, might explain why since 2000 only a limited number of studies about personalised pricing have been published.

Nonetheless, some interesting and relevant studies have been carried out which are worth mentioning here. In the 2014 study by Hannak et al. (also mentioned in the price steering section above), research with real user accounts showed **few inconsistencies in product prices** (typically <0.5% of products, see Figure below), although some evidence for personalised pricing was found on a home improvement site, a department store, and several of the travel sites (all in the US). However, since real users' data were not collected in experimental setting, the study was unable to identify the user characteristics that led to differential pricing. On the other hand, in the same study by Hannak et al., a **controlled experiment did identify some cases of sites altering product prices which could be linked to personal characteristics:**

⁶⁹ Van Tien Hoang, Vittoria Cozza, Marinella Petrocchi and Rocco De Nicola. 'Online user behavioural modelling with applications to price steering' (Jun 2016). Link: http://www.iit.cnr.it/sites/default/files/priceFINREC.pdf

OFT(2013), "The economics of online personalised pricing", Report
 OECD, Directorate for Financial and Enterprise Affair, Competition Committee, "Price discrimination". Background note by the Secretariat. 29-30 November 2016. Available at: https://one.oecd.org/document/DAF/COMP(2016)15/en/pdf

 $^{^{72}}$ Chapter 7 explains in more detail the possibilities and constraints of companies in using price personalisation. 73 OECD (2016b) referenced above 71

⁷⁴ CNN Law Center (2005), "Web sites change prices based on consumers' habits". 24 June 2005. Available at: http://edition.cnn.com/2005/LAW/06/24/ramasastry.website.prices

- on 1 travel website ("Cheaptickets.com/Orbitz.com"⁷⁵) logged-in users received different prices on ≈5% of hotels;
- on 1 travel website ("Travelocity.com") it was measured that prices fell by \approx \$15 on \approx 5% of hotels (or on approx. 3 out of 50 per page) for iOS users; and
- on 1 general retailer website ("HomeDepot.com"), the "Android treatment" consistently saw differences on $\approx 6\%$ of prices (one or two products out of 24). However, the average price differential observed for Android users was very low ($\approx 0.41).

The general level of price discrimination by website as measured by Hannak et al. is presented in the figure below:

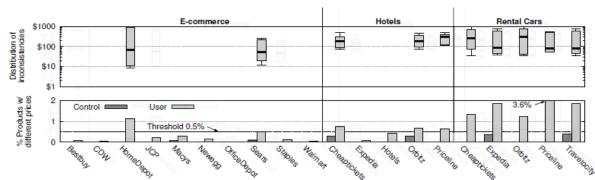


Figure 10: Occurrence of price discrimination in 16 e-commerce websites

Figure 3: Percent of products with inconsistent prices (bottom), and the distribution of price differences for sites with $\geq 0.5\%$ of products showing differences (top), across all users and searches for each web site. The top plot shows the mean (thick line), 25th and 75th percentile (box), and 5th and 95th percentile (whisker).

Source: Hannak et al. (2014)⁷⁶

The 2012 study by Mikians et al., mentioned also in the section on personalised offers, found no evidence of price personalisation either based on system preferences (OS/browser) or on previous browsing behaviour / personal attributes (affluent, budget conscious). However, the study did observe signs of price discrimination based on geographical location on 2 online vendors⁷⁷. In addition, the study finds evidence that if the shopper is referred to the e-commerce website by a price comparison website (PCW), they tend to see both lower prices for identical products compared to shoppers who access the e-commerce website directly. For one website, for some product categories, when a user visited the website via a discount aggregator site, the prices observed were 23% lower as compared to visiting the same vendor site directly.

Researchers have produced a browser add-on called "\$heriff"⁷⁸ which can detect if a website offers different prices to customers based in different locations, taking into account currency differences, see figure 10 for an illustration. Based on research with this tool, **Iordanou et al. (2017)**⁷⁹ **reported users seeing differences in prices depending on their country of origin or the type of browser used. However, this was a marginal phenomenon:** Out of a total of 1,994 websites checked by real users using "\$heriff", 24

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⁷⁵ The study by Hannak et a;. (2014) noted: "These sites [Cheaptickets/Orbitz] are actually one company, and appear to be implemented using the same HTML structure and server-side logic".

⁷⁶ Hannak et al.

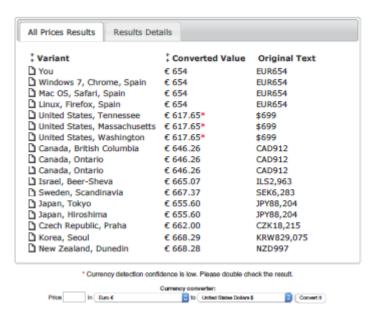
⁷⁷ Signs of price discrimination based on geographical location were found on the online vendors: "Shoplet.com" and "Discountofficeitems.com". See Mikians et al. 2012 referenced above.⁶⁵

Nikolaos Laoutaris, 'The Vision for a Data Transparency Lab': From Price Discrimination to Data Transparency, Telefonica Research, TMA2015, Barcelona. http://tma-2015.cba.upc.edu/images/TMA/Presentations/The%20vision%20for%20a%20Data%20Transparency%20Lab.pdf

⁷⁹ Costas Iordanou, Claudio Soriente, Michael Sirivianos, Nikolaos Laoutaris, "Who is Fiddling with Prices?: Building and Deploying a Watchdog Service for E-commerce". Available at: http://laoutaris.info/wp-content/uploads/2017/07/sigcomm17-final89.pdf

websites showed signs of price variation, and only 2 websites showed signs of price discrimination within the same country (i.e. price differences not linked to geo-localisation or explicable by other factors such as VAT differences)⁸⁰.

Figure 11: Results with detected currencies



Source: Iordanou et al, "Who is Fiddling with Prices?"81

Earlier research by Mikians et al. (2013)⁸² analysed the frequency and the magnitude of price variation observed in a crowdsourced dataset (collected using the \$heriff tool also used for Iordanou et al. study above), allowing contributions from other Internet users to the dataset. This research showed that for most e-retailers between 10%–30% of price variations could not be attributed to currency, shipping, or taxation differences. The results also showed that the physical (IP address based) location played a role in price variations for different categories of products. On the other hand, the study found no price differences when using "trained personas" which reflected affluent and budget conscious users. Being logged in to an account or not did also show no or little correlation with price variations. Mikians et al. concluded that more research needed to be carried out to look whether the observed price variations mentioned above could be attributed to the personal information of a user (e.g., websites visited, purchases performed, etc.).

Another study conducted in 2013 by the French data protection regulator and the French Ministry of Economy and Finance found evidence of a number of personalisation practices in the ecommerce sector in France⁸³. For example, **important variations in prices were**

⁸⁰ In total 3 websites showed price differences within the same country. For 1 of these 3 websites ("Amazon"), differences in prices could be linked to differences in VAT scales across countries; which could hence not be qualified as personalised pricing. For one of the other two websites, chegg.com (an online textbook rental company), in Spain, the UK, and Germany, a 3% to 7% price difference for the same product was detected in the same country. On the third website, "Jcpenney.com", price differences measured within the same country were below 2% in Spain, France, and Germany, and exactly 7% in the UK. See Iordanou et al. (2017)⁷⁹.

⁸¹ Iordanou et al⁷⁹

⁸² Mikians, J., L. Gyarmati, V. Erramilli, and N. Laoutaris, 'Crowd-assisted search for price discrimination in e-commerce: First results' (2013). Link: http://conferences.sigcomm.org/co-next/2013/program/p1.pdf

⁸³ La Commission nationale de l'informatique et des libertés (CNIL) et la Direction générale de la Concurrence, de la Consommation et de la Répression des Fraudes (DG CCRF), « IP Tracking: conclusions de l'enquête conjointe menée par la CNIL and la DGCCRF ». Available at :

 $https://www.economie.gouv.fr/files/files/directions_services/dgccrf/presse/communique/2014/cp_tracking_27012014.pdf$

detected in the travel sector, based on the number of places left in the concerned means of transport (plane or train) or the time of the day that a ticket was purchased (e.g. prices were lower during peak hours) - both of which would qualify as dynamic pricing. The study also found evidence of personalised pricing based on browser history or the use of a price comparison tool. Users of the latter were offered cheaper products, however with more elevated additional fees; the total price paid was on average not significantly different.

A more recent study conducted in 2016 for the German Advisory Council for Consumer Affairs (SVRV) on personalised pricing in the online market⁸⁴ found that personalised pricing occurs in the tourism sector, based on user-related features. For example, luxury users paid more than non-luxury ones (e.g. €2,230 versus €2,196)85. Furthermore, personalised pricing was found in the airlines sector and for holiday packages, where Windows users consistently recorded lower prices compared to Apple users. The study did not detect price discrimination in other sectors (such as consumer electronics, sporting goods, fashion, toys, insurance, pharmaceutical products etc.). Based on these findings, the SVRV concluded that the conducted experiments suggested that the prevalence of price differentiation based on personal data in Germany is low.

On another note, a 2016 Mystery Shopping carried out by the Commission looked at prices charged to online consumers for the same product but as part of the way territorial restrictions are applied at different stages during the online cross-border shopping process of consumers. The Mystery Shopping, carried out on more than 10,000 websites at EU level identified that when domestic prices found on e-commerce product pages were compared to prices reported after cross-border registration for shoppers, price differences were found in 20% of cases: for 13% cross-border prices were higher, while for 7% domestic prices were higher.86 But here of course the practices as such related to some form of geo-identification of the consumer and not to consumers' browsing history or sociodemographic characteristics.

⁸⁴ Michael Schleusener, Sarah Hosell, "Personalisierte Preisdifferenzierung im Online-Handel". January 2016. http://www.svr-verbraucherfragen.de/wp-content/uploads/eWeb-Research-Available at: Center Preisdifferenzierung-im-Onlinehandel.pdf

⁸⁵ Schleusener & Hosell

⁸⁶ GfK (2016) on behalf of the European Commission, Mystery Shopping survey on Territorial Restrictions and geo-blocking in the European Digital Single Market.

Online sellers: Type of personal data collected, transparency in communication and compliance with relevant EU and national legislation

This Chapter focusses on identifying how online personalisation practices work, how data is collected for these practices, and how online personalised practices might develop in the future. In addition, it is assessed whether businesses clearly communicate personalised practices and if sellers' online personalised practices comply with the existing EU regulatory framework for data protection and consumer protection. This chapter is mainly based on findings from the literature review, supplemented by findings from the stakeholder survey. The Chapter contains the following main sections:

- Type of personal data collected on consumers and the means for collecting data by online sellers/providers (Section 3.1);
- The overall data market ecosystem and the use and transmittance of personal data by online sellers/providers for personalisation of their services and offers (Section 3.2);
- The transparency of online sellers/providers using personalisation practices towards consumers and their compliance with the relevant EU regulatory framework (Section 3.3); and
- The future evolution of the online market as a result of technological advances (Section 3.4)

This Chapter aims to answer the research questions from the Terms of Reference listed below. These are referred to as "RQ" in the text.

Table 5: Research Questions covered in this Chapter

Research Question	Section addressing question
RQ2. What type of personal data do online firms collect in order to provide personalised prices/offers to consumers? How sensitive ⁸⁷ is this information?	3.1.1
RQ3. What are the means of collecting this information? Is this done by the online firms themselves or do they procure it from other companies which specialise in such collection	3.1.2
RQ4. Are companies using these techniques transparent about their data collection methods and the (further/subsequent) use of consumers' personal data? How exactly do they communicate about their pricing methods? Do companies that collect data for personalised pricing/offers transmit this data? If yes, to whom? Do companies transmit ⁸⁸ the consumer profiles relating to their consumers?	3.3
RQ5. In the case of marketplaces, is the data used for personalised pricing by a seller on that marketplace solely collected by that seller? Is the consumer data at the disposal of the marketplace	3.2.3

⁸⁷ In line with the definition of sensitive data, provided by the EU data protection framework. See Art 9 of the Regulation (EU) 2016/679 and Art 8 of the Directive 95/46/EC

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⁸⁸ See above⁸⁷

Research Question	Section addressing question
transmitted, partially or entirely, to the sellers on that marketplace? If yes, what information is transmitted, how is it transmitted and how transparent is the marketplace vis-à-vis consumers regarding the sharing of consumer data?	
RQ6. Are businesses which monitor consumers' online behaviour and use this information to offer personalised prices/offers complying with consumer laws and existing EU regulatory framework ⁸⁹ ?	3.3.1
RQ7. Which consumer profiles are used across online markets for personalising prices/offers, which parameters are used and how are they interpreted? How are algorithms built? Are they built in house or outsourced? Do businesses target certain types of consumers more or differently? How dynamic are the consumer profiles? Do they continuously/frequently change over time, adapting to new personal data?	3.1.1 3.1.2
RQ10. Are there available tools that allow consumers to prevent such personalisation? If yes, are they widely used?	3.1.2
RQ11. How are personalisation techniques likely to evolve, especially with the emergence of the Internet of Things and of Artificial Intelligence? Are personalised pricing/offers likely to further develop in the near future and become the typical pricing model of online sellers or is it likely to remain a pricing method limited to a small minority of online sellers.	3.4

3.1. Type of personal data collected for online personalisation and means of collecting such data

The General Data Protection Regulation (GDPR) defines personal data as follows: "any information relating to an identified or identifiable natural person ('data subject'); an identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person"⁹⁰.

The collection of personal data and the profiling of consumers is enabled by the amount of data generated by multiple devices and the advances in tracking technologies and data analytics. This has led to the emergence of new data-driven business models that focus on understanding the consumer to offer better tailored products and services⁹¹, and to

⁸⁹ The study aimed to assess business operators' compliance with the relevant consumer protection and data protection EU regulatory framework.

Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data. Available at http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R0679&from=EN

OECD, Directorate for Science, Technology and Industry, Committee for Information, Computer and Communications Policy "Exploring the economics of personal data: a survey of methodologies for measuring monetary value", 2013. Available at: http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DSTI/ICCP/IE/REG(2011)2/FINAL &docLanguage=EN

determine with greater accuracy the optimal prices to offer to consumers according to their profile⁹². Many business models have also evolved to monetise data or for revenue optimisation. Christl et al. (2017) summarise the data collection and tracking practices of online companies as follows: "Based on data and guided by their business interests and economic goals, companies have constructed an environment in which individuals are constantly surveyed and evaluated, investigated and examined, categorized and grouped, rated and ranked, numbered and quantified, included or excluded, and, as a result, treated differently"⁹³.

While such online personalised practices are not illegal a priori, they might cause issues for consumers related to data collection, transparency and protection. In this context, the next sections explore the type of personal data collected on consumers (3.1.1) and the tracking technologies used for collecting and analysing data (3.1.2).

3.1.1. Type of personal data collected for personalisation

As noted by for example the *Harvard Business review* (2017), online retailers aim to determine consumers' willingness to pay for certain products or services, based on consumers' specific online characteristics and behaviour (e.g. consumers' location, device used, operating system, products viewed etc.) and subsequently offer tailored prices to the different consumer profiles⁹⁴. But **what type of personal data do online firms collect to provide personalised prices/offers to consumers? And is this sensitive information** (see RQ2 listed above)? To answer these research questions, this sub-section looks more in detail at the types of personal data collected as well the user profiles resulting from/ based on the data collected.

The data collection *possibilities* on the online market are virtually infinite. This is due to the proliferation of tracking and data-matching technologies (see for more details Section 3.1.2), but also because internet users often provide the data themselves without necessarily realising they will be used for different purposes. According to the OECD (2013)⁹⁵, personal data can be **volunteered or surrendered** by individuals themselves (e.g. providing personal information when creating users' accounts online, publishing on social media or blogs etc.), **observed** (e.g. captured while tracking users' browsing activity, location data or purchase history via loyalty schemes etc.)⁹⁶ or **inferred** (obtained after analysing and combining different parameters). Data is often collected, analysed and further transmitted to online sellers or other parties from specialised companies (e.g. data brokers), collected from business partners (e.g. Facebook shares data with a broad range of third parties and advertisers⁹⁷) or through mergers and acquisitions. The ways data are obtained and combined from various sources in order to profile users are explored later in this Chapter.

⁹² Adam Tanner, Forbes (2014), "Different Customers, Different Prices, Thanks to Big Data". 14 April 2014. Available at: https://www.forbes.com/sites/adamtanner/2014/03/26/different-customers-different-prices-thanks-to-big-data/#4e25a32a5730

⁹³ Wolfie Christl, Cracked Labs (2017), "Corporate surveillance in everyday life: How companies collect, combine, analyse, trade, and use personal data on billions". Report. Available at: http://crackedlabs.org/dl/CrackedLabs Christl CorporateSurveillance.pdf

⁹⁴ Harvard Business Review (2017), "How retailers use personalized prices to test what you're willing to pay". 20 October 2017. Available at: https://hbr.org/2017/10/how-retailers-use-personalized-prices-to-test-what-youre-willing-to-pay

⁹⁵ OECD (2013) report referenced above⁹¹.

⁹⁶ Section 3.1.2 explores in more details the technologies used for data collection and profiling consumers.

⁹⁷ Facebook Data Policy, "Sharing With Third-Party Partners and Customers" states that the Facebook-owned companies share information with advertisers as well as with "Vendors, service providers and other partners. We transfer information to vendors, service providers, and other partners who globally support our business, such as providing technical infrastructure services, analyzing how our Services are used, measuring the effectiveness of ads and services, providing customer service, facilitating payments, or conducting academic research and surveys." Available at: https://www.facebook.com/policy.php

Do online firms also make use of these possibilities, i.e. do they indeed collect this data? The answer appears to be "yes". The table below illustrates the preponderance of data types collected on consumers, based on the combined findings from studies from the UK Competition and Markets Authority (2015)⁹⁸ and Rao et al⁹⁹.

Table 6: Data collected by firms for commercial purposes

Table 6: Data collected by firms for commercial purposes					
Data category	Examples of type of data collected per category*				
Financial and transactional data	 Information on income and credit ratings 				
Transactional data	 History of purchases via loyalty cards, completed online and/or prices paid 				
Contact information	Individual's home/work addressEmail addressPhone number				
Socio-demographic data	 Age Ethnicity Gender Level of education Occupation and social class (e.g. sector, net worth associated with a specific profession) Household Income Number of family members (e.g. number, gender and age of children) Religion 				
Contractual data	 History from utility suppliers, contract service details 				
Location data	 Mobile devices Vehicle telematics GPS data and history of/planned journeys entered into the satellite navigation system Sensor data (from radio-frequency identification (RFID) 				
Behavioural and interests' data	 History of visited websites and clicks on advertisements (which could include searches on sensitive topics such as health problems or political views) Games and applications used Telematics data from automotive insurance companies Posts on social media, professional websites and blogs Email exchanges 				
Technical data	 IP address Data related to the device (e.g. type, international mobile equipment identity (IMEI)) Browser information 				

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⁹⁸ Competition & Markets Authority (2015), "The commercial use of consumer data", Report on the CMA's call for information. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/435817/The_commercial_use_of_consumer_data.pdf

⁹⁹ Ashwini Rao, Florian Schaub and Norman Sadeh, Carnegie Mellon University: "What do they know about me? Contents and concerns of Online Behavioural Profiles". 30 July 204. Available at: https://www.cylab.cmu.edu/files/pdfs/tech-reports/CMUCyLab14011.pdf

Data category	Examples of type of data collected per category*
Data related to social relationships	 Links between family members and friends
Open data and public records	 Birth and death records Marriages Electoral registers Court and insolvency records Land registry records
Data transmitted online /stored by users on devices or the "cloud"	 Audio-visual media (e.g. photos, videos etc.)

^{*} List is non-exhaustive.

Source: Table elaborated based on the findings from the followings studies: Competition & Markets Authority (2015), "The commercial use of consumer data" and Rao et al. "What do they know about me: Contents and concerns of Online Behavioural Profiles".

The data categories presented above are supported by numerous additional sources¹⁰¹ as well as the stakeholder survey¹⁰². Therefore, the findings overwhelmingly point to the fact that potentially *any* type of personal data is collected. This brings us to the second part of RQ2, does the data collected include sensitive information about the individual?

Sensitivity of the data collected by online companies

It is important to note that the GDPR (applicable as of the 25 May 2018) prohibits the processing of special categories of personal data (sensitive data), based on "racial or ethnic origin, political opinions, religious or philosophical beliefs, or trade union membership, and the processing of genetic data, biometric data for the purpose of uniquely identifying a natural person, data concerning health or data concerning a natural person's sex life or sexual orientation" 103 unless one of the exception applies. The processing of sensitive data is also prohibited under the **EU Data Protection Directive 95/46/EC**104 (Art 8); however, the new Regulation includes additional categories such as genetic and biometric data. Furthermore, the **ePrivacy Directive**105 prohibits any interference with the confidentiality of communications and the related traffic data by persons other than users, without the consent of the users concerned, except when legally authorised to do so (Art 5). In addition, the Directive postulates that "the use of electronic communications networks to store information or to gain access to information stored in the terminal

For more details on the type of data collected, please refer to: OECD report (2010) 91 and Wolfie Christl, Sarah Spiekermann (2016), Networks of Control. A report on corporate surveillance, digital tracking, Big Data & Privacy. Wien 2016. Available at: http://crackedlabs.org/dl/Christl Spiekermann Networks Of Control.pdf

¹⁰⁰ Competition & Markets Authority (2015) referenced above⁹⁸

According to the DPAs and national experts that replied, business operators collect any type of data, depending on the services they wish to offer. According to the consulted stakeholders, this includes: contact details (e.g. email address), personal details (e.g. name, age, sex), consumer preferences and interests, social media and behavioural data, search history, time of visits/purchase, demographic data, location and physical address, the route via which the consumer has arrived to the website (e.g. whether the referring website is a price comparison tool or a competitor's website), device and browser information, IP address, keywords used in conversations online, health and financial data collected through online questionnaires which is consequently used for targeted marketing.

¹⁰³ The GDPR referenced above⁹⁰

Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995 on the protection of individuals with regard to the processing of personal data and on the free movement of such data. Available at: http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:31995L0046:en:HTML

¹⁰⁵ Directive 2002/58/EC of the European Parliament and of the Council of 12 July 2002 concerning the processing of personal data and the protection of privacy in the electronic communications sector ('Directive on privacy and electronic communications'). http://eurlex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:32002L0058:en:HTML

equipment of a subscriber or user is only allowed on condition that the subscriber or user concerned is provided with clear and comprehensive information in accordance with Directive 95/46/EC, inter alia about the purposes of the processing, and is offered the right to refuse such processing by the data controller."(Art 5(3))¹⁰⁶. Thus, any user "information" (including personal and non-personal data) which is accessed or stored in terminal equipment falls under the scope of the ePrivacy Directive (for more information on the relevant legal framework, see Section 3.3.1 and Annex 2). These requirements are maintained by the Commission proposal for a Regulation on the respect for private life and the protection of personal data¹⁰⁷ in electronic communications from January 2017.

In relation to the **sensitivity of the data collected on consumers** (RQ2), the desk research showed that companies collect data on topics such as health, political views or sexual orientation for online targeted advertising. An article published by the *Economist* in 2014 on data gathering practices argued that, although many advertisers claim not to have interest in keeping sensitive data and do not use it, there is evidence of companies applying targeted advertisement based on personal health data¹⁰⁸. A study by Carrascosa et al. (2014) that aimed to measure and capture the magnitude of online behavioural advertising (OBA)¹⁰⁹, showed that up to 40% of the online adverts displayed to vulnerable users located in Spain were associated with OBA¹¹⁰. The study showed that personal treats particularly prone to be targeted by OBA linked to health related personal characteristics (cancer, HIV, infectious diseases, genetic disorders, etc.).

In the stakeholder consultation (DPAs and national experts surveys) 2 of the respondents advocated that sensitive data is indeed collected by online firms. One of the respondents noted that data that is not per se sensitive in itself, could become sensitive when triangulated with other information available on the consumer.

Why do companies collect data on topics such as health, political views or sexual orientation for online targeted advertising, despite such tracking being generally prohibited under the European data protection framework? The main reason appears to be that sensitive data is more valuable on the data market, as it provides more detailed information about the individual and thus, allows digital marketers to target consumers better¹¹¹. Carrascosa et al. (2014) could observe a marked correlation between the level of received OBA and the value of the persona for the online advertising market (based on the suggested Cost per Click bid for each of the personas in the Google AdWords keyword planner tool).

Although the above shows that the type of personal data collected for online personalisation can be sensitive, it should be noted that the purpose of personalisation is not generally to reveal the identity of the individual, but to be able to segment users. The UK Office of Fair Trading (OFT) identified in 2013 a general trend related to personalised pricing: businesses are more interested in identifying "different sorts of customers and segment their customer base into fine groups, rather than seeking to identify who individuals are"112. Three experts consulted for the current

Proposal for a Regulation of the European Parliament and of the Council concerning the respect for private life and the protection of personal data in electronic communications and repealing Directive 2002/58/EC (Regulation on Privacy and Electronic Communications). Available here: https://ec.europa.eu/digital-single-market/en/news/proposal-regulation-privacy-and-electronic-communications

 $^{^{106}\,} Idem^{105}$

Amendments to the proposal by the European Parliament and the Council were adopted in October and December 2017, respectively.

The Economist, "Getting to know you", September 2014. Available at: http://www.economist.com/news/special-report/21615871-everything-people-do-online-avidly-followed-advertisers-and-third-party
For a definition of online behavioural advertising, please refer to Terminology (Section 1.4).

J. M. Carrascosa, J. Mikians, R. Cuevas, V. Erramilli, N. Laoutaris, "I Always Feel Like Somebody's Watching Me. Measuring Online Behavioural Advertising," ACM CoNEXT'15. Available at: https://conferences2.sigcomm.org/co-next/2015/img/papers/conext15-final80.pdf

¹¹¹ Emily Steel, Financial Times, "Financial worth of personal data comes in under a penny a piece". Article. 12 June 2013. Available at: https://www.ft.com/content/3cb056c6-d343-11e2-b3ff-00144feab7de

OFT (2013), "Personalised Pricing: Increasing Transparency to Improve Trust", Report. Available at:http://webarchive.nationalarchives.gov.uk/20140402142426/http://www.oft.gov.uk/shared_oft/markets-work/personalised-pricing/oft1489.pdf.

study supported that traders do not necessarily seek to know sensitive personal details on individuals or to identify the person whose data has been collected (e.g. by name). Instead, companies focus on obtaining information on their interests and certain type of characteristics that could allow traders to personalise their offers more accurately. Three companies that offer personalisation solutions and were interviewed for this study specified that they collect data in anonymous or "pseudoanonymous" format (e.g. the databases do not contain the names, email addresses etc.) and that they cannot identify the person whose data has been collected. The intentional identification of individuals represents a more refined method.

Although anonymisation (and to a lesser extend pseudonymisation, see below) techniques reduce the data protection risks for consumers, these techniques may not fully guarantee data privacy. The distinction between personal and non-personal data becomes less clear if pseudonymisation and anonymisation techniques are not applied properly, as they can be reversed to allow to identify the individual. The next sub-section focusses on the impact of pseudonymisation and anonymisation techniques on the consumers' data protection.

De-anonymisation and re-identification of individuals based on collected data

Some desk research indicated that companies tend to use data which is pseudonymous rather than anonymous¹¹³. The main difference between "anonymization" and "pseudonymisation" lays in the possibility of re-identification of the data subject. According to the GDPR, anonymised data "does not relate to an identified or identifiable natural person or to personal data rendered anonymous in such a manner that the data subject is not or no longer identifiable" and hence does not fall under the scope of the Regulation¹¹⁴. Thus, anonymisation should prevent the re-identification of the individual even in cases of aggregating and combining information on individuals obtained from different sources.

Pseudonymisation, on the other hand, offers more limited privacy protection and involves "the processing of personal data in such a manner that the personal data can no longer be attributed to a specific data subject without the use of additional information"¹¹⁵ (Article 4(5), GDPR). Therefore, pseudonymisation is achieved by replacing the identifying characteristics, but allows for the indirect identification of the individuals. As noted in an Article 29 Data Protection Working Party (Article 29 WP) Opinion, "pseudonymization is not a method of anonymization. It merely reduces the "linkability" of a dataset with the original identity of a data subject, and is accordingly a useful security measure."¹¹⁶ Pseudonymisation falls under the scope of the GDPR (Recital 26)¹¹⁷.

Anonymisation techniques could still entail privacy and data protection risks for consumers. For example, the Article 29 WP recognises that anonymisation techniques "can provide privacy guarantees and may be used to generate efficient anonymisation processes, but only if their application is engineered appropriately"¹¹⁸. The Opinion states further that properly anonymised datasets should not allow companies to re-identify individuals by:

¹¹³ Wolfie Christl p.69 referenced above⁹³

¹¹⁴ Recital 26 of the GDPR (referenced above)⁹⁰ states in relation to anonymisation that "The principles of data protection should therefore not apply to anonymous information, namely information which does not relate to an identified or identifiable natural person or to personal data rendered anonymous in such a manner that the data subject is not or no longer identifiable. This Regulation does not therefore concern the processing of such anonymous information, including for statistical or research purposes."

¹¹⁵ GDPR referenced above⁹⁰

Article 29 Data Protection Working Party, "Opinion 05/2014 on Anonymisation Techniques", Adopted on 10 April 2014. Available at: http://ec.europa.eu/justice/data-protection/article-29/documentation/opinion-recommendation/files/2014/wp216_en.pdf

Personal data which have undergone pseudonymisation, which could be attributed to a natural person by the use of additional information should be considered to be information on an identifiable natural person.

¹¹⁸ Opinion 05/2014 referenced above¹¹⁶.

- "Singling out" isolating the records of an individual in a dataset;
- "Linkability" linking two records concerning the same data subject, or a group of data subjects, in the same of different datasets; or
- "Inference" the possibility to deduce with significant probability, the value of an attribute from the values of a set of other attributes 119

Therefore, the Opinion concludes that "as long as the data is identifiable, data protection rules apply", and warns against using pseudonymous and anonymous techniques interchangeably¹²⁰.

Furthermore, claims of anonymity can be misleading¹²¹ as the datasets at disposal of companies can often be de-anonymised by combining information from different sources and linking anonymous data (e.g. financial records) with personally identifiable information (e.g. name, address)¹²². While the findings from the literature as well as the business operators consulted for this study suggest that companies usually remove the names collected on individuals and encrypt other personal identifiers (e.g. addresses, phone numbers), these "hashed" identifiers can still be linked across other online services and databases and matched to a profile¹²³.

Moreover, individuals' names are not necessarily the only and most important parameter that allow the re-identification of a person. For example, earlier studies showed that combining the date of birth, gender and zip code are enough to accurately identify an individual – such information allowed for the unique identification of 87% of the United States population (216 million of 248 million in 2000)¹²⁴. Identification was even possible with less precise identifiers (e.g. city or country), in combination with birthdate and gender¹²⁵. In addition, retailers can combine zip codes with information captured at stores' points-of-sale (e.g. name, telephone number, credit card details) to determine the home address of the individual ^{126,127}. As noted above, due to the amount of data available on consumers from multiple online sources and the risks of re-identification of individuals, "the distinction between anonymous information and personal data has become less clear" (Datatilsynet 2015)¹²⁸.

How is data used for consumer profiling

As noted above, the evidence suggests that any type of personal data can be and is collected online. This raises the question which consumer profiles are used in practice across online markets for personalising prices/offers, which parameters are used and how are they interpreted (RQ7)?

The creation of detailed online profiles comes as a natural consequence of the preponderance of consumer data collected across the Web and the data-matching resources (e.g. via data brokers or aggregators) available online. According to the Danish Data Protection Agency (Datatilsynet¹²⁹) a profile is "made up of assumptions about the preferences, abilities or needs of an individual or a group of individuals. The interferences

¹²⁰ Idem¹¹⁶

¹¹⁹ Idem¹¹⁶

 $^{^{121}}$ The level of transparency of companies towards consumers is explored in further details in Section 3.3

¹²² Rao et Al referenced above⁹⁹

¹²³ Rao et Al referenced above⁹⁹

Latanya Sweeney, Simple Demographics Often Identify People Uniquely. Carnegie Mellon University, Data Privacy Working Paper 3, Pittsburgh 2000. Available at: https://dataprivacylab.org/projects/identifiability/paper1.pdf

¹²⁵ Sweeney (2000) referenced above 124

¹²⁶ Adam Tanner, Forbes (2013), "Never Give Stores your zip code. Here's why". Available at: https://www.forbes.com/sites/adamtanner/2013/06/19/theres-a-billion-reasons-not-to-give-stores-your-zip-code-ever/#70291b6c786f

 ¹²⁷ Chris Jay Hoofnagle, Behavioural Advertising: The Offer you can't refuse, 6 Harv.L.& Pol'y Rev.273(2012).
 Available at: http://scholarship.law.berkeley.edu/cgi/viewcontent.cgi?article=3086&context=facpubs
 128 Datatilsynet (2015)⁵⁸

¹²⁹ Official website: https://www.datatilsynet.dk/english/the-danish-data-protection-agency/introduction-to-the-danish-data-protection-agency/

are made from analysis of individuals' browsing history, updates on social media, which news articles they read, products bought on the Internet and registered customer information. Nowadays profiling is to a great extent about using Big Data analysis to look for patterns and connections in large data sets which can be used to predict consumer behaviour"¹³⁰.

Which parameters are used and how are they interpreted? (RQ7) Online companies record consumers' behaviour and interests to identify consumption patterns and consumption power. Rao et al¹³¹ describe how technical data such as IP addresses can be used to deduce information about individual's names, postal address, purchase history and subsequently purchasing power. Behavioural data and important "life event information" (e.g. marriages, pregnancy, purchasing of real estate property, marriage, divorce etc.) can provide important information on an individual's purchasing power or purchasing intentions¹³². Health data can be also collected for predictive health marketing purposes and to target consumers with mobiles adverts related to specific health conditions¹³³. There are reported cases of retailers being able to predict the birth of a child, based on women's purchase or search history (e.g. baby clothes, specific nutritional supplements or cosmetics)¹³⁴.

On the other hand, it should be noted that online profiles often lack accuracy. As confirmed by our study's experts and the literature, a recurring problem for those using online profiles is that these contain errors and inconsistencies, hence limiting their usability¹³⁵ ¹³⁶.

Do businesses target certain types of consumers more or differently? (RQ7) The findings from desk research as well as from the experts' consultation suggest that they do. For example, research by Carrascosa et al. showed that some profiles are targeted more than others, depending on the economic value of the data involved in the profiles¹³⁷. The findings from the literature review as well as the experts' consultation suggest that certain parameters in consumer profiles may be assumed to predict "wealth" or higher willingness to pay, and therefore lead to consumers paying more, depending on their device 138 or location (e.g. neighbourhoods that are considered "wealthy" 139). Two stakeholders interviewed for the current study mentioned that companies sometimes target specific socio-demographic groups such as senior citizens, students or young people, or potentially people with handicaps (without providing further examples). According to companies, this is often done with the aim to offer these citizens better targeted discounts. However, it could well be the case that online firms can take advantage of their position and exploit the weakness of certain types of consumers who may have less experience in online markets. For example, it is possible that data on consumers' health (e.g. allergies, disabilities, diabetes) or certain habits or interests that could be perceived as weaknesses (e.g. smoking, gambling, interest in weight loss) is collected and later used to target the

¹³⁰ Datatilsynet (2015)⁵⁸

¹³¹ Rao et al. referenced above⁹⁹

¹³² Charles Duhigg, How Companies Learn Your Secrets. New York Times, 16 February 2012. Available at: http://www.nytimes.com/2012/02/19/magazine/shopping-habits.html

AdAge, "Data partners to tie mobile ads to drug refills, doc visits". March 2016. Available at: http://adage.com/article/dataworks/data-partners-tie-mobile-ads-drug-refills-doc-visits/302937/

¹³⁴ Idem¹³²

¹³⁵ Forbes Insights and Criteo (2017), "The Commerce Data Opportunity: How collaboration levels the retail playing field". Report. Available at: https://www.criteo.com/news/press-releases/2017/10/criteo-and-forbes-study-commerce-data-opportunity/

¹³⁶ Rao et al. referenced above⁹⁹

¹³⁷ Carrascosa et al referenced above⁴⁶

¹³⁸ See for instance Russon, M.A. (November 2014), "Mac and Android Users Charged More on Shopping Sites Than iPhone and Windows Users Look Out, You Might be Charged More If You Shop Online Using a Mac or Android Device". International Business Times. Available at: http://www.ibtimes.co.uk/look-out-you-might-be-charged-more-if-you-shop-online-using-mac-android-device-1474431

¹³⁹ According to experts consulted for the study.

individuals with related offers such as dietary products, medications, food supplements etc. 140.

A 2013 OECD¹⁴¹ report noted that loyalty schemes are a common data source used in particular by online retailers to create consumers' profiles in order to target them better with loyalty discounts, offers, and to decrease transaction costs for both consumers and sellers. There is evidence that loyalty programs along with data marketing have intensified in recent years.¹⁴²

3.1.2. Technologies used for collecting personal data

As mentioned earlier, the profiling of consumers is enabled by the variety of available tracking and data-matching technologies online. This sub-section details some of the most commonly used technologies for the collection of data and focusses on the **means of collecting consumers' information (RQ3) from a technological perspective and whether this is done by online firms themselves or they procure it from other companies which specialise in such data collection, as well as on the way algorithms are used in practice on the online market (RQ7).**

In the era of the "Internet of things" (IoT), a vast range of "smart" technologies and objects are available to collect online data from computers, smartphones and wearables, smart TVs, various sensors and smart home appliances, etc. These devices often store significant amounts of data on consumers' daily and personal lives, habits and even appearance (e.g. photos, video, facial detection features) as well as technical information allowing to pinpoint the devices (e.g. MAC addresses, IP addresses). Furthermore, devices are usually connected (e.g. via Wi-Fi, Bluetooth, Near-field communication (NFC)) and thus, capable of transmitting information to other devices or systems. Consequently, tracking technologies can easily follow the average consumer across websites, platforms devices and provide companies with data on a person's online as well as offline lifestyle. By making use of machine learning algorithms, companies can create more refined profiles of consumers.

As mentioned before, certain types of data, and particularly data related to a person's identity or online transactions, are collected through means of explicit declaration by the customer himself, or by a third party to whom the data was volunteered or "surrendered" (e.g. registration forms, credit card information entered at the time of purchase etc.)¹⁴³. In addition, information is often inferred by combining and analysing data collected on consumers by other background mechanisms from different sources, often without the consumers' knowledge. For example, a study conducted by the *Wall Street Journal* in 2010 showed that the top 50 US websites install 64 pieces of tracking technology on average, in most cases without notifying the user¹⁴⁴. An overview of the main technologies used for tracking and profiling consumers is presented below.

Wolfie Christl, Sarah Spiekermann (2016), "Networks of Control". Available at: http://crackedlabs.org/dl/Christl Spiekermann Networks Of Control.pdf

¹⁴¹ OECD (2013) report referenced above⁹¹

¹⁴² Cracked Labs (2017) report references above⁹³

¹⁴³ Please see OECD (2013) report referenced above⁹¹

¹⁴⁴ Angwin, J. (2010), "The Web's New Gold Mine: Your Secrets," Wall Street Journal, Available at: https://www.wsj.com/articles/SB10001424052748703940904575395073512989404

Figure 12: Technologies used to track users

Tracking mechanisms	Technologies
Tracking meenanisms	recimologics
Fingerprinting	
Network and location	IP address, server-based geolocation techniques, HTTP
fingerprinting	headers, HTML5, JavaScript, Flash, Java
Device fingerprinting	IP address, TCP headers, HTTP headers, JavaScript, Flash
Operating system instance fingerprinting	JavaScript, Flash, Java, ActiveX
Browser version fingerprinting	HTML5, JavaScript, CSS
Browser version fingerprinting using web history	Server-side measurements, HTTP headers, JavaScript
Browser instance fingerprinting using canvas	HTML5, JavaScript
Other browser instance fingerprinting methods	HTTP headers, JavaScript, Flash
Session-only	Mah saman sassian
Session identifiers stored in hidden fields	Web-server session
Explicit web-form authentication	Web-server session
Window.name DOM property	HTML5, JavaScript
Storage-based	
HTTP cookies	HTTP headers, JavaScript
Flash LocalConnection Object	Flash
Flash cookies and Java JNLP PersistenceService	Flash / Java
Silverlight Isolated Storage	Silverlight
HTML5 Global, Local and	HTML5, JavaScript
Session Storage	.,
Web SQL. Database and HTML5 Indexed database	HTML5, JavaScript
Internet Explorer userData storage	JavaScript
Cache-based (Web cache)	
Embedding identifiers in cached documents	HTML5, JavaScript
Loading performance tests	Server-side measurements, JavaScript
ETags and Last-modified headers	HTTP headers
Cache-based (DNS lookups)	JavaScript
Cache-based (Operational caches)	
HTTP 301 redirect cache	HTTP headers
HTTP authentication cache	HTTP headers, JavaScript
HTTP Strict Transport Security cache	HTTP headers, JavaScript
TLS Session Resumption cache and TLS Session IDs	Web-server session
Other tracking mechanisms	

Tracking mechanisms	Technologies
Headers attached to outgoing HTTP requests	HTTP headers
Using telephone metadata	Smartphone malware
Timing attacks	HTML5, JavaScript, CSS
Using unconscious collaboration of the user	HTML5, JavaScript, CSS, Flash
Clickjacking	HTML5, JavaScript, CSS
Evercookies (supercookies)	Web-server session, HTML5, JavaScript, Flash, Silverlight, Java

Source: Bujlow et al. (2015), "Web Tracking: Mechanisms, Implications, and Defenses" 145

The next sub-sections explore in further detail some of the most widespread tracking technologies listed above.

The most traditional background tracking technology is cookies ¹⁴⁶ - the core of what *The Wall Street Journal* (2010) describes the 'tracking industry'. Cookies are small "pieces of data" in the form of text files that are stored on a computer or a mobile device when a user visits a website. The cookie collects data on the user such as user ID, time and date of visiting a website/clicking on the advert and location, based on the IP address. The behaviour of the user can be tracked (provided that he or she does not delete the cookie) when they visit websites, e.g. those part of Google's service Ad sense¹⁴⁷, and thus, over time they can be profiled and segmented based on their preferences. Information on individual users is not transmitted to third parties; however, advertisers in the network can access data in aggregated form¹⁴⁸. The stakeholder interviews confirmed that most business operators (7 out of 10) reported that online firms mainly use cookies.

There are different types of cookies depending on their lifespan or domain hosting them¹⁴⁹. In terms of lifespan, cookies can be **session cookies** (transient, i.e. erased once a browser is closed) or **persistent (or permanent) cookies** which are stored on the user's device for a certain time, for a year or more, unless refused or deleted by the individual¹⁵⁰.

In terms of the main hosting domain, cookies can be first-party and third-party. First-party cookies are those placed by the visited website. The information gathered might help the publisher to improve its services and products and target users with offers and advertising. Third-party cookies however are hosted "by a domain that is not the same as the visited page's domain"¹⁵¹. They are usually present on dozens of websites, placed by actors active in the areas of market analysis, and targeted marketing. In doing so they can extensively track a user's behaviour and come up with elaborated profiles. Another study conducted in 2009 showed examples of first-party and third-party actors setting different tracking cookies¹⁵². For instance, Google Analytics sets first-party cookies with Javascript code by a third party. On the other hand, third party cookies are set by advertising marketplaces such as Doubleclick which allows publishers to use behavioural targeting through special

¹⁴⁹ The EU Internet Handbook, "Cookies": http://ec.europa.eu/ipg/basics/legal/cookies/index en.htm

¹⁴⁵ Tomasz Bujlow, Valentín Carela-Español, Josep Solé-Pareta, Pere Barlet-Ros, Web Tracking: Mechanisms, Implications and Defenses. July 2015. Available at: https://arxiv.org/pdf/1507.07872.pdf

¹⁴⁶ See a more in-depth description in European Commission, "Cookies". Available at: http://ec.europa.eu/ipg/basics/legal/cookies/index_en.htm

AdSense (Google) is a program that allows website owners to earn revenues from their ad space by displaying targeted ads for the visitors of their websites. AdSense selects the ads through a real-time ad auction and automatically displays the bid "winners" on the website: https://support.google.com/adsense/answer/6242051?hl=en

¹⁴⁸ Adsense website referenced above ¹⁴⁷

¹⁵⁰ For example, the cookies sweep conducted by the Article 29 Working Party, identified cookies expiring in year 9999. See: http://ec.europa.eu/justice/data-protection/article-29/documentation/opinion-recommendation/files/2015/wp229_en.pdf.

¹⁵¹ The EU Internet Handbook referenced above ¹⁴⁹

B.Krishnamurthy and C.Willis, "Privacy diffusion on the web: a longitudinal perspective" in Proceedings of the 18th international conference on the World Wide Web. ACM, 2009. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.232.3038&rep=rep1&type=pdf

Doubleclick cookies¹⁵³. Another example is Quantserve¹⁵⁴ that uses a combination of first-party and third-party cookies as well as Javascript code.

Thus, the most intrusive monitoring comes from third-party cookies a fortiori if they are resistant. The Article 29 Working Party study established that 70 % of the recorded cookies (on average 35 per website) across nearly 500 websites were third-party cookies and tended to be of the persistent type. These cookies are "used among others by advertising networks to monitor users' behaviour and better target their advertisements over time"¹⁵⁵. In the report on personalised pricing¹⁵⁶, the OFT observed third party cookies on multiple websites through a cookie detection application. They compared the results with cookie notices and privacy policy information on the websites. Their findings showed that there was a discrepancy between the cookies listed and the ones detected by the cookie application. They also concluded that "the policies often did not inform the consumer of the nature of them" which leads to confusion for consumers"¹⁵⁷.

Cookies have their limitations since they can be deleted or blocked easily. In the consumer survey for this study, slightly less than a third (30%) of respondents answered that they always or very often delete cookies. In order to bypass these constraints, online companies can use more sophisticated technologies that enable them to continue tracking users even after the deletion of regular cookies. One such example is a more resilient type of cookie ("evercookie" or "supercookie") which uses "various storages in order to survive or rebuild after deletion, or even reproduce in other browsers used at the same computer." Other more refined methods include tracking using the combination of IP address and Web beacons and browser fingerprinting, described in the sections below.

IP address and Web beacons

Another way to track online data is via a user's IP (Internet Protocol) address. The IP address provides information about the user's location and his network. The IP address has the benefit of being easily retrievable, and can deliver detailed information about the user when used in combination with web beacons. Web beacons are invisible graphic images embedded in a website or an email, which can be used on their own or in combination with cookies. Once a page containing a web beacon is opened, a request is sent to the graphic image owner's server for an image, allowing the owner to track the event along with other information (IP address, time, browser...). It is important to note that it is not possible to shield oneself from web beacons, as opposed to cookies 160. An example of a company using web beacons is Quantserve, owned by the behavioural advertising company Quantcast 161. The company transmits collected data in aggregated form to third parties for targeted adverts 162.

¹⁵³ Joana Geary, The Guardian (2012), "DoubleClick (Google): What is it and what does is it do?". Available at: https://www.theguardian.com/technology/2012/apr/23/doubleclick-tracking-trackers-cookies-web-monitoring

¹⁵⁴ The Guardian, Quantserve (Quantcast): What is it and what does it do? 23 April 2012. Available at: https://www.theguardian.com/technology/2012/apr/23/quantcast-tracking-trackers-cookies-web-monitoring

European Parliament Research Service (EPRS) 2017, Review of the ePrivacy Directive, Briefing. Available at: http://www.europarl.europa.eu/thinktank/en/document.html?reference=EPRS BRI(2017)587347

¹⁵⁶ OFT (2013)112

¹⁵⁷ OFT(2013)¹¹².

¹⁵⁸ Bujlow et al¹⁴⁵

¹⁵⁹ Datatilsynet referenced above⁵⁸

¹⁶⁰ Datatilsynet referenced above, p. 20⁵⁸

¹⁶¹ See https://www.quantcast.com/

¹⁶² James Ball, Joanna Grey, The Guardian (2012), "Quantserve (Quantcast): What is it and what does it do?". Available at: https://www.theguardian.com/technology/2012/apr/23/quantcast-tracking-trackers-cookies-web-monitoring

Fingerprinting

Another tracking technology used by the advertising industry in particular is **digital fingerprinting**¹⁶³, which plays an important part in linking digital profiles across websites¹⁶⁴. This technique makes use of the unique electronic fingerprint each device leaves when connected to the internet. It is based on variety of technical and usage parameters (examples presented in Figure 12). Parameters that when combined leave a unique fingerprint include **system-type data** (e.g. OS, local time, type of device, language settings, IP address, MAC address) **and usage-type of data** (e.g. HTTP headers containing information on the date, time and settings; browser type and version, the specific webpage visited by the user, even typing frequency)¹⁶⁵ ¹⁶⁶.

A study on the uniqueness of web browsers and fingerprinting¹⁶⁷ found that most tested browsers (83.4% from a sample of 470,161 browsers) had a unique identifiable fingerprint; this included users that had disabled Adobe Flash or Java for privacy purposes (without this group 94.2% of browsers had a unique identifiable fingerprint).

In contrast to cookies, the user cannot easily refuse or block device fingerprinting and typically the average user is not or is hardly aware such tracking is occurring¹⁶⁸. Furthermore, algorithms were still able to follow users even when there were changes in the fingerprints¹⁶⁹. Thus, fingerprinting can allow marketers to create a "persistent" ID of consumers across the web. As a result, companies are able to build profiles and to resolve consumers' identity across devices and platforms, either through their own technologies or through using the services of specialised companies¹⁷⁰ ¹⁷¹ (RQ3, RQ7).

Although the use of fingerprinting, as well as cookies, has to comply with the EU data protection and e-Privacy legal framework, individual's privacy is potentially threatened. The Article 29 Working Party has made a recommendation in relation to device fingerprinting. It concludes that the rules for cookies should also apply to device fingerprinting i.e. that consent must be obtained before information about the user's device is collected.

Algorithms used

The increased interconnectivity of individuals and businesses via the growing number of smart devices and the amount of data generated in the process has led to the emergence of an "algorithmic business", which can be defined as "the use of complex mathematical algorithms pivotal to driving improved business decisions or process automation for competitive differentiation"¹⁷². Algorithms used in **predictive analytics** play a particularly important role in predicting consumers' behaviour and preferences. The use of algorithms also allows businesses to gain competitive advantage by optimising their business processes, for example by reducing production and transaction costs, segmenting more accurately consumers, setting prices to respond to market demands¹⁷³.

¹⁶³ Forbes (October 2012), "Big Data: Deciphering Digital Marketing Intelligence (Part 1 of 2)", Brent Gleason,. Available at: http://www.forbes.com/sites/brentgleeson/2012/10/10/big-data-deciphering-digital-marketing-intelligence-part-1-of-2/2/#3cced1915959/

¹⁶⁴ Christl et al referenced above p.69⁹³

¹⁶⁵ Martin Kihn, Gartner for Marketers , How Cross-Device Identity Matching works (part 1 and part 2). 2016. Available at: https://blogs.gartner.com/martin-kihn/how-cross-device-identity-matching-works-part-1/ and https://blogs.gartner.com/martin-kihn/how-cross-device-identity-matching-works-part-2/

¹⁶⁶ Peter Eckersley, Electronic Frontier Foundation (2010), "How Unique is Your Web Browser". Available at: https://panopticlick.eff.org/static/browser-uniqueness.pdf

¹⁶⁷ Please see Eckersley (2010) referenced above ¹⁶⁶

¹⁶⁸ Bujlow et al (2015) referenced above ¹⁴⁵

¹⁶⁹ Please see Eckersley (2010) referenced above ¹⁶⁶

¹⁷⁰ One such example are Criteo's commerce marketing solutions: https://www.criteo.com/

¹⁷¹ See for example BlueCava http://bluecava.com/our-solutions/ or Drawbridge: https://www.drawbridge.com/

¹⁷² Garner IT Glossary: https://www.gartner.com/it-glossary/algorithmic-business

OECD(2017), Algorithms and Collusion: Competition Policy in the Digital Age. Available at: http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm

More specifically, algorithms allow companies to organise information more efficiently, discover patterns and draw valuable insights, based on data. The OECD has conducted extensive research and consultation on the topic¹⁷⁴. An OECD (2017) report on algorithms and competition policy argued that the impact of algorithms on the demand and supply side of the market also results in benefits for the end consumer¹⁷⁵. For example, by lowering production costs through more efficient allocation of resources, online firms can also offer lower prices to consumers. In addition, accurate insights on consumer preferences can lead to improved quality of services for consumers (e.g. better search engine results or personalised shopping recommendations)¹⁷⁶. In addition, they can be used to calculate the probability of a person buying airline tickets or car insurance, based on their previous behaviour¹⁷⁷. Price comparison websites (PCW) can also improve their recommendations to consumers by implementing algorithms and consequently, help consumers to make better informed purchasing decisions¹⁷⁸. Predictive analytics have important applications for targeted advertising and product recommendation.

Pricing algorithms are also commonly used for dynamic pricing and price discrimination¹⁷⁹. The OECD (2017) report highlights that among the advantages of pricing algorithms' is their ability to "automatically set prices to maximise profits" due to their computational power to process large amounts of data and by adapting quickly to changing market conditions¹⁸⁰. Being automated, they may also be able to identify more effectively different consumers' willingness to pay or switch providers and set prices accordingly. As a result, according to Oxera, they have the potential to "reflect the true cost" of a service to an individual¹⁸¹. Therefore, as suggested by a series of OECD background papers (2016)¹⁸² 183, algorithms can result in "perfect price discrimination"¹⁸⁴. One way consumers benefit from this, especially those with lower willingness to pay, is by being offered lower prices. Additional literature further suggests that algorithms will have an increasing role in consumers' decision-making process ("algorithmic consumers")185. For example, algorithms can speed up and optimise consumers' decision-making process by analysing more decision parameters in less time, as well as by offering new perspectives that a human might have otherwise missed. Furthermore, algorithms can help consumers avoid manipulative marketing techniques (e.g. based on people's emotions, fears or aspirations) or individual biases¹⁸⁶, but on the other hand they might as well exploit them (see below).

Desk research shows that **algorithms also have their disadvantages for sellers as well as for consumers**. For instance, pricing algorithms could lead to discrimination based on gender, race or other illegal discriminatory practices (explored in more details in Section 3.3.1). In addition, sellers that do not implement pricing algorithms can also be in a disadvantageous position in comparison with those who do¹⁸⁷. This observation is further supported by additional literature. A study conducted in 2015 for detecting algorithmic

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 $^{^{174}}$ See for example: OECD (2017) 173 , OECD (2016a) 182 and OECD (2016b) 183

¹⁷⁵ OECD 2017¹⁷³

¹⁷⁶ OECD 2017¹⁷³

¹⁷⁷ Rao et al. referenced above⁹⁹

¹⁷⁸ OECD 2017¹⁷³

¹⁷⁹ Oxera (2017). "When algorithms set prices: winners and losers". Discussion paper. June 2017. Available at: https://www.oxera.com/getmedia/3243dc6d-9c69-4292-8b47-4366d18903d1/When-algorithms-set-prices-winners-and-losers.pdf.aspx?ext=.pdf

¹⁸⁰ OECD 2017¹⁷³

¹⁸¹ Oxera (2017)¹⁷⁹.

¹⁸² OECD (2016a), "Big Data: Bringing Competition policy to the Digital Era". Background Note by the Secretariat. Available at: https://one.oecd.org/document/DAF/COMP(2016)14/en/pdf

OECD (2016b), Roundtable on Price Discrimination. Background note by the Secretariat. Available at: https://one.oecd.org/document/DAF/COMP(2016)15/en/pdf

 ¹⁸⁴ OECD(2016b)¹⁸³
 185 Michal S.Gal & Niva Elkin-Koren. "Algorithmic consumers". Harvard Journal of Law & Technology. Volume 30, Number 2 Spring 2017. Available at: http://jolt.law.harvard.edu/assets/articlePDFs/v30/30HarvJLTech309.pdf

¹⁸⁶ Gal & Elkin-Koren (2017)¹⁸⁵

¹⁸⁷ OECD 2017¹⁷³

pricing 188 found that algorithmic sellers on Amazon marketplace receive more feedback on average and win the Amazon Buy Box^{189} more frequently than non-algorithmic ones. As algorithm-based processes are automated, sellers using them are able to adapt and change their products' prices several hundreds times per day – something that non-algorithmic sellers can hardly achieve.

Mislove et al. (2016) note that algorithms may lead to market distortion, for example by setting unrealistically high prices or implement price fixing 190. The paper argues that the impact of dynamic pricing on consumers is unclear, as sellers do not necessarily sell their items at the lowest price – on the contrary, the study found evidence that some traders sell at 40% higher than the initial minimum price set for the product. Consumers may also receive recommendations/offers that do not accurately reflect their preferences as algorithms have limitations in predicting some nuances in human's behaviour or run privacy and cyber-security risks¹⁹¹. These technological limitations could lead to biases or errors that the consumers might not even be aware that they are experiencing. Furthermore, pricing algorithms may pose challenges for regulators as well since it is difficult to assess based on what parameters are algorithms setting prices¹⁹². Mislove et al. (2016) also suggest that there is a need for additional research in order to understand better the impact algorithmic pricing may have on consumers. There is an inherent transparency risk in algorithms which depends on the algorithm's design¹⁹³. For example, another study that provides a typology of pricing algorithms¹⁹⁴ argues that some algorithms may be less transparent than others such as those at advertising auctions¹⁹⁵.

Companies are already making use of the pricing algorithms described above¹⁹⁶. One example is the machine-learning company Blue Yonder providing Artificial Intelligence (AI) price optimisation solutions for the retail sector¹⁹⁷. Their algorithms automatically set the optimal price for the different channels and products tailored to consumer demand by taking into account internal data (retailers' products, sales data, brand etc.) as well as external data (e.g. competitors' prices, weather, holidays' or other events information). As a result, retailers can improve predictions of consumers' purchasing intentions in their stores, differentiate better their prices as well as optimize their internal processes.

Another example is Amazon Marketplace and the Buy Box algorithm (mentioned above)¹⁹⁸. Le Chen et al. (2016)¹⁹⁹ methodology provided insights into the potential mechanism behind the Buy Box algorithm. The study identified the algorithmic pricing strategies by 500 sellers and observed that the algorithm chooses the Buy Box winner mainly based on the price, the feedback on the sellers as well as the number of positive feedback the seller has received. A third example is the machine-learning company Criteo which offers personalisation solutions for e-commerce companies and advertisers²⁰⁰. The company's solutions link real-time information on consumers across different browsers, devices and

¹⁸⁸ Le Chen, Alan Mislove, Christo Wilson. "An Empirical Analysis on Algorithmic Pricing on Amazon Marketplace". In Proceedings of the International World Wide Web Conference (WWW' 16), Montreal. Canada, Apr 2016. Available at: https://mislove.org/publications/Amazon-WWW.pdf

¹⁸⁹ The Buy Box algorithm is the mechanism determining which seller among many of the same product will be included in product page (Buy Box) where consumers can add products to their shopping carts: https://www.amazon.com/qp/help/customer/display.html?nodeId=200401830

¹⁹⁰ Mislove et al referenced above 188

¹⁹¹ Gal & Elkin-Koren (2017)¹⁸⁵

¹⁹² Oxera (2017) report¹⁷⁹

¹⁹³ Gal & Elkin-Koren (2017)¹⁸⁵

¹⁹⁴ Oxera (2017) report^{179.}

¹⁹⁵ For more details on the typology of pricing algorithms, please refer to Oxera (2017) report^{179.}

¹⁹⁶ It is important to note that companies are generally reluctant to share information regarding their algorithm's design, which they consider sensitive information or Intellectual Property (IP). Thus, the findings related to the mechanisms behind algorithms presented in this sub-topic are based on literature, results from the stakeholder consultation and from other studies that have encountered similar challenges in obtaining more detailed information on algorithms' functionalities such as Oxera (2017) report¹⁷⁹

¹⁹⁷ Blue Yonder official website: https://www.blue-yonder.com/en

¹⁹⁸ Buy Box: https://www.amazon.com/qp/help/customer/display.html?nodeId=200401830

¹⁹⁹ Le Chen et al (2016)¹⁸⁸

²⁰⁰ Criteo official website : https://www.criteo.com/

apps and allow companies to tailor product recommendations and display the most relevant content. Companies such as Uber, Airbnb, advertising platforms and airline companies also use algorithmic pricing²⁰¹.

Stakeholder interviews confirmed that the algorithms used to analyse individuals' behavioural data and create consumers' profiles are often completely automated and could be adapted according to the sector and the needs of the companies using them. Furthermore, e-commerce websites quite often outsource the development of such algorithms to specialised companies according to half of the respondents (e.g. data analytics companies or technology companies providing personalisation solutions/services) as retailers often do not have the resources to collect/analyse the data themselves (RQ7). As a result, e-commerce companies are able to reduce costs and gain access to higher quality data. However, it was also noted that the challenge for e-commerce websites is to ensure that the firm they are collaborating with is a trusted party, which will perform the data gathering and personalisation in compliance with existing data protection legislation.

Technologies used by consumers to protect themselves

As observed in the above sections, the technologies used for collecting personal data and profiling consumers are ubiquitous and these processes are often running in the background without consumers' awareness. However, are there tools to help consumers achieve the opposite and prevent online tracking and personalisation? (RQ10). This subtopic focusses on the available tools that enable users to protect their privacy.

Studies show that consumers are willing to look for anonymisation solutions online, even though they do not believe that complete anonymity is possible²⁰². Protection against online tracking is however a multi-step approach and can be fostered by using a combination of services and tools, rather than relying solely on one solution.

For example, as a first step to protect themselves, consumers can use the private browsing mode²⁰³ (available in all web browsers) which stores only temporary data (e.g. cookies) until the user quits the browser or alternatively, they can enable their browser to delete cookies each time it closes. However, it is to be noted that private browsing offers only limited protection against more advanced tracking technologies (e.g. it doesn't prevent fingerprinting). Furthermore, the level of protection that private browsing offers differs across different browsers (e.g. Safari's private browsing was found to be less restrictive for a number of tracking technologies in a 2015 study on web tracking mechanisms)²⁰⁴. The figure below illustrates to what extent private browsing protects users against different tracking technologies (where "Yes/No" indicates whether tracking a user in private browsing with a given technology is possible or not):

Pew Research Center, Anonymity, Privacy and Security Online (2013). Available at http://www.pewinternet.org/2013/09/05/anonymity-privacy-and-security-online/

²⁰¹ Oxera (2017) report¹⁷⁹.

Forbes (2017). What is Private Browsing and Why Should You Use it? Available at: https://www.forbes.com/sites/leemathews/2017/01/27/what-is-private-browsing-and-why-should-you-use-it/#1784a4cb25b1

²⁰⁴ Tomasz Bujlow, Valentín Carela-Español, Josep Solé-Pareta, Pere Barlet-Ros, Web Tracking: Mechanisms, Implications and Defenses. July 2015. Available at: https://arxiv.org/pdf/1507.07872.pdf

13: Private browsing mode and tracking mechanisms are

	and tracking mechanisms protection
Tracking mechanism	Tracking a normal-mode user identity in a private browsing mode
Fingerprinting	
Device fingerprinting	Yes
Network and location fingerprinting	Yes
Operating system instance fingerprinting	Yes
Browser version fingerprinting	Yes
Browser instance fingerprinting using canvas	Yes
Browser instance fingerprinting using web browsing history	Yes – In Safari No - In Chrome, Firefox and IE
Other browser instance fingerprinting methods	Yes
Storage-based	
HTTP cookies	Yes – in Safari No – in Chrome, Firefox and IE
Flash cookies	Yes – in Safari No – in Chrome, Firefox and IE
Flash LocalConnection Object	Yes
Silverlight Isolated Storage	Yes – in Safari No – in Chrome, Firefox and IE
HTML5 Global, Local and Session Storage	Yes – in Safari No – in Chrome, Firefox and IE
Web SQL. Database and HTML5 Indexed database	Yes – in Safari No – in Chrome, Firefox and IE
Internet Explorer userData storage	No
Cache-based (Web cache)	
Embedding identifiers in cached documents	Yes – in Safari No – in Chrome, Firefox and IE
Loading performance tests	Yes – in Safari No – in Chrome, Firefox and IE
Cache-based (DNS lookups)	Yes
Cache-based (Operational caches)	
HTTP 301 redirect cache	Yes – in Safari No – in Chrome, Firefox and IE
HTTP authentication cache	Yes – in Safari No – in Chrome, Firefox and IE
HTTP Strict Transport Security cache	Yes – in Safari No – in Chrome, Firefox and IE
Other tracking mechanisms	Voc
Headers attached to outgoing HTTP requests	Yes
Timing attacks	Yes – in Safari No – in Chrome, Firefox and IE
Evercookies (supercookies)	Yes – in Safari No – in Chrome, Firefox and IE

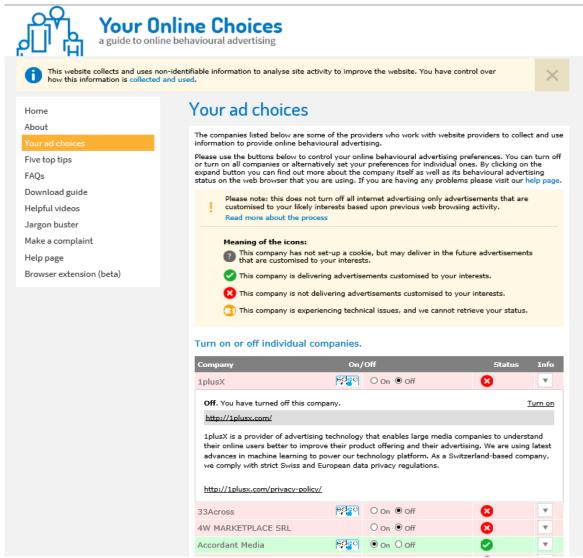
Source: Bujlow et al. (2015), "Web Tracking: Mechanisms, Implications, and Defenses" 205

 $[\]frac{205}{1}$ Bujlow et al. $(2015)^{204}$

An additional method for consumers to prevent being tracked is to use the "do-not-track" (DNT) function²⁰⁶ in their browser, which activates a so called "HTTP header field" that requests that a web application disable either its tracking or cross-site user tracking. However, this privacy enhancing function depends on the implementation by websites and it has been noted in the literature that DNT requests have a minimum impact on OBA as they have not been sufficiently enforced yet, thus online advert companies and websites tend to bypass them²⁰⁷.

There are also tools that allow users to deactivate advertising on a tracker by tracker basis, such as Your Online Choices industry-led platform by the European Advertising Standards Alliance (EASA) and the Interactive Advertising Bureau (IAB) ²⁰⁸. Using these tools, the user can read more information related to each advertising trackers, before deciding to disable the specific tracker or not. An example of the options available to consumers is presented below.

Figure 14: Reviewing the list of advertising trackers



Source: Your Online Choices: a guide to online behavioural advertising 209

However, in an Opinion from 2011 the Article 29 Working Party has noted that the "choice" "follows an opt-out approach and thus is not consistent with the requirement for prior

https://www.eff.org/issues/do-not-track

²⁰⁷ Carrascosa et al⁴⁶

²⁰⁸ http://www.youronlinechoices.com/lu-fr/controler-ses-cookies

²⁰⁹ http://www.youronlinechoices.com/lu-fr/controler-ses-cookies

informed consent as set out in article 5(3) of the revised e-Privacy Directive"²¹⁰. Furthermore, the Opinion brought the attention to additional problems with the functionalities platform in relation to the requirements of the ePrivacy Directive (Art 5(3)). For example, opting out prevents future personalised pricing from the disabled trackers, but does not prevent accessing and storing information on the user's terminal. Moreover, users are not informed whether the cookies remain stored on their devices, the purpose for which they are still stored/accessed or the ways to previously installed cookies can be managed or deleted²¹¹.

In relation to price discrimination, the stakeholder consultation also suggested that there are tools that both consumers and regulators can use for the detection of this practice. One such example is the **\$heriff**²¹² extension available for Google Chrome which allows consumers to compare differences in prices when the same product on an online retailer website has been accessed by different browsers or locations. Another similar tool is "**Pricius**"²¹³ which automatically collects and analyses e-commerce websites information to detect price discrimination and geo-blocking, or **Aditau**r²¹⁴ which automates the detection of targeted advertising.

In addition to the tools described above, consumers can make use of the following practices and technologies to prevent being tracked online:

- **Alternative search engines** that do not track users or use digital fingerprints such as DuckDuckgo²¹⁵, FindX²¹⁶, Qwant²¹⁷, Hulbee²¹⁸ or Startpage²¹⁹.
- **Virtual Private Network (VPNs**) tools that establish secure encrypted communication channels with selected servers (usually operated by the VPN provider) and prevent other parties, including the Internet Service Providers (ISPs), to track and intercept their communication.
- **Additional web tracking defences** (among presented in Bujlow et al. (2015))²²⁰ such as: 1) TaintDroid²²¹, which allows mobile users to monitor the way different applications use their data; 2) Lightbeam²²², an extension which shows users their interaction with first-party and third-party sites; 3) MindYourPrivacy²²³, which presents visually user's web trackers; and 4) tools like Adblock, Ublock, Ghostery or Privacy Badger²²⁴, which are browser plugins that block tracking cookies and scripts from running by default.

In relation to the above it should be mentioned that these tools require a 'tech savviness' / knowledge about online tracking which the average consumer may not have. In the consumer survey for this study, 60% of respondents indicated to never use or to don't know about tools to hide their IP address such as VPNs or the Tor browser. A further 17% said to only rarely use these tools. Slightly less than half (45%) of respondents indicated

²¹⁰ Article 29 Working Party, Opinion 16/2011 on EASA/EAB Best Practice Recommendation on Online Behavioural Advertising". 8 December 2011.

²¹¹ Opinion 16/2011²¹⁰

²¹² "\$heriff – Detecting Price Discrimination," 2014. [Online]. Available at: http://sheriff.dynu.com/views/home

http://www.lstech.io/pricius-regulation

²¹⁴ http://www.lstech.io/aditaur

https://duckduckgo.com/

²¹⁶ https://www.findx.com/

²¹⁷ https://www.qwant.com/

https://swisscows.com/ https://www.startpage.com/

²²⁰ Bujlow et al. (2015)¹⁴⁵

²²¹ W. Enck, P. Gilbert, B.-G. Chun, L. P. Cox, J. Jung, P. McDaniel, and A. N. Sheth, "Taintdroid: an information flow tracking system for real-time privacy monitoring on smartphones," Communications of the ACM, vol. 57, no. 3, pp. 99–106, 2014.

Lightbeam for Firefox," 2014. [Online]. Available: https://addons.mozilla.org/en-US/firefox/addon/lightbeam
 Y. Takano, S. Ohta, T. Takahashi, R. Ando, and T. Inoue, "Mindyourprivacy: Design and implementation of a visualization system for third-party web tracking," in Privacy, Security and Trust (PST), 2014 Twelfth Annual International Conference on. IEEE, 2014, pp. 48–56.

²²⁴ Kiran Garimella et al., "Ad-blocking: A Study on Performance, Privacy and Counter-measures" (May 2017). Available at: https://arxiv.org/pdf/1705.03193.pdf

to never use or don't know about other apps/plugins designed to protect privacy online, whilst another 20% indicated to only rarely use these tools. The low actual awareness about cookies measured in the consumer survey suggests, moreover, that even when consumers claim to be aware about certain tools they might not actually be aware about how they work or should be used. See Sections 4.8 and 4.9.

The above findings show that as a result of the detailed data collected on consumers and sophisticated analytics and tracking technologies, the distinction between personal and non-personal data becomes blurred in practice, despite the fact that the EU data protection legal framework is based on the distinction between the two notions. The next section explores in further detail this complex data ecosystem.

3.2. The overall data market ecosystem and whether companies transmit the data used for personalisation purposes

The data market has allowed the online retail and advertising business to evolve significantly in the past years via the collection, aggregation, analysis, usage and trading of data in a highly complex ecosystem, involving a multitude of actors. These sections seek to provide a better understanding of:

- The ways companies procure themselves with/collect consumers' data (either using their own means or though the services of other specialised companies) (RQ3);
- The practices where companies that collect data for personalised pricing/offers transmit this data or consumers' profiles (RQ4); and
- Whether platforms or other marketplaces transmit data to the sellers on that marketplace (RQ5).

The following three sections focus on answering these research questions. Section 3.2.1 focuses on providing an overview of the data market main actors and the personal data value chain. Section 3.2.2 explores the practices where online business operators transmit consumer data to other actors in the market. Section 3.2.3 focusses on the specific case of consumers' data being transmitted and used by online marketplaces and commercial platforms.

3.2.1. The personal data value chain in the online data market

To assess to what extent personal data is transmitted by companies in the online market (RQ4 and RQ5), it is important to understand the data market ecosystem and the ways the different actors interact in the personal data value chain.

What is the impact of the availability of personal data in the market? The desk research showed that data is increasingly becoming an asset and is of a great monetary value. **Essentially, data is becoming the basis for the emergence of new data-driven business models, focused on understanding the individual consumers**. From a company's perspective, the understanding of customers based on data is one of the top challenges and priorities for marketers in order to achieve better consumer segmentation and targeting, according to the Gartner 2016 Multichannel Marketing Survey²²⁵. As a result, behavioural data collected from first-party and third party sources is becoming increasingly important²²⁶. As demonstrated later in this Chapter (Section 3.2.2.) data is often transmitted to various types of interested first- and third- parties.

67

²²⁵Gartner for Marketers, "Multichannel Marketing Primer for 2016". Available at: https://www.gartner.com/binaries/content/assets/qml/ki-pages/research-primers/493d9b1f-5864-4210-84ed-adf13f25fc27 gartner for marketers multichannel marketing primer.pdf

²²⁶ Gartner For Marketers report (2016) referenced above²²⁵

What are the different steps and actors involved in the personal value data chain? The literature shows that data collection is only the starting point of a specific data value chain that includes a variety of actors who may be involved in the collection, and transmission of data (explained later in this Chapter). A 2013 OECD report²²⁷ summarised this complex ecosystem using the figure shown below:

Collection / Storage and Analysis and Personal data Usage distribution aggregation access Volunteered •Mobile phones •ISPs and phone •Retailers and Businesses e.g. declared providers service providers hobbies and Blogs and Government and interests. publicsector discussion lists •Government Public preferences, agencies (e.g. tax administration agencies expertise, etc. offices, property Social. professionaland registries, etc.) •End users. Financial special interest institutions networks •On-line social Observed networks, •Healthcare e.a. location User-generated providers information, •Financial content browser history. Specialized institutions shopping habits Lovalty schemes companies operated by •Medical involved in online retailers practitioners advertising and market research, Inferred Smart appliances Utility service e.g. credit ratings, providers Data analysts providers and profiles built from Applications online activities, brokers •Retailers

Figure 15: Personal data value chain

etc

•Sensors etc.

Source: OECD (2013), "Exploring the economics of personal data: a survey of methodologies for measuring monetary value"

Data collection refers to the data "harvesting" process. According to the OECD report on the economic value of personal data and their impact on the future online economy, the process of data collection "covers all sectors of the economy and data is gathered from a myriad of sources" ^{228.} A firm that collects data could be a first party with direct relationship with the customer, or alternatively could collect the customers' data through third parties and marketplaces that specialise in data gathering and refinement (RQ3) ²²⁹.

Data storage and aggregation involves data collectors investing in storage facilities, leasing shared storage capacity, or outsourcing the management of the data entirely, including its storage, to specialised intermediaries. Users' data can be stored by a wide range of services providers such as Internet Service Providers, online retailers,

This report scrutinized different data sources such as call logs, location, customer identification, logon and transaction information, browser history, page visits, purchases, app access and their impact on the future online economy. See: OECD, Directorate for Science, Technology and Industry, Committee for Information, Computer and Communications Policy "Exploring the economics of personal data: a survey of methodologies for measuring monetary value", 2013. Available at: http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DSTI/ICCP/IE/REG(2011)2/FINAL &docLanguage=EN

This report scrutinized different data sources such as call logs, location, customer identification, logon and transaction information, browser history, page visits, purchases, app access and their impact on the future online economy. See: OECD, Directorate for Science, Technology and Industry, Committee for Information, Computer and Communications Policy "Exploring the economics of personal data: a survey of methodologies for measuring monetary value", 2013. Available at: http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DSTI/ICCP/IE/REG(2011)2/FINAL &docLanguage=EN

²²⁹ Analysis Mason on behalf of Ofcom (2014), "Online data economy value chain". Report. Available at: https://www.ofcom.org.uk/__data/assets/pdf_file/0019/80272/annexes_to_analysys_mason_report_online __customer_data.pdf?lang=cym

transportation firms, medical practitioners, utilities and government agencies. User generated and submitted content can also be stored by a range of service and content providers, including social networks.

Data processing and analysis is about applying analytical techniques to data in order to obtain a better understanding of customers through analysing patterns and correlations of online behaviour. Such insights can be easily exchanged and transmitted, as they tend not to include any personal data. Data use and monetisation create a "new revenue stream or enhance an existing one, thus monetising the data to its full potential in the value chain, according to Ofcom." 230

As indicated in the 2013 OECD report²³¹, collected and stored data can be combined (or enriched) with additional online and offline sources and subsequently transmitted to other parties, typically in anonymised (or as noted in Section 3.1.1, pseudonymous) form. The OECD report states that insights obtained at the data processing and analysis stage of the data value chain can be used to establish more refined personal profiles which are often resold in the market. This work is often done by data analytics firms with developed infrastructure, strong analytical skills and developed distribution networks.

A study from the OFT²³² schematises the data sharing practices in the value chain in the following way: "Information about a consumer's interaction with a business is often captured by an online retailer when a consumer is searching or shopping online, for example, their interest in a particular company or product. The business now holding this information has a potentially valuable commodity, which it may wish to use for its own analytical research and/or may pass on to other businesses (third parties) which operate in a market for consumer information. These third parties might offer data-analysis services, or may combine or aggregate the information with other, additional information, or offer data analysis tools. All of these services help to optimise the value of the information and may make the collected information more useful to retailers."²³³

The literature shows that businesses in almost all sectors are involved in the data market. Especially active in the data market appear to be businesses in the retail, travel, consumer goods, media, telecommunications and marketing sectors²³⁴. The marketing data and advertising industry is among the largest sectors in this ecosystem, which encompasses various actors, such as marketing agencies, data brokers, online advertisers, and ecommerce companies²³⁵ (examples of the actors in the advertising ecosystem are presented in the "Targeted advertising section").

The figure below provides an overview of the main actors involved in the data business.

²³⁰ Ofcom(2014) referenced above²²⁹.

²³¹ OECD (2013).

²³² OFT(2013)¹¹².

²³³ OFT(2013)^{112.}

²³⁴ Christl (2017) referenced above⁹³

²³⁵ Christl (2017) referenced above⁹³

Large-scale collection COMMERCIAL Mobile China and use of data on Mobile Carriers Telefónica **DIGITAL TRACKING AND** people, often without TELECOM, DEVICE, AND Google their knowledge **PROFILING LANDSCAPE** SERVICE PROVIDERS Alibaba Facebook Wearables Smart Amazon Connected Verizon LARGE Car AOL. Yahoo Apple PLATFORMS In recent years, CONSUMER DATA AND ANALYTICS MOUSTAL TELCO/MEDIA Tencent most industries Comcast **NBC** Universal have joined today's Softbank Naspers TSTA pervasive personal TimeWarner data ecosystems ADVERTISING TECHNOLOGY Microsoft Online Payment Services Publishers Video Games CUSTOMER Credit Card Services Websites BUSINESS IT MANAGEMENT CRM Brokers Companies Fintech Music DATA alth & Insurance INTEGRATION Walt MEDIA AND Salesforce **FINANCIAL SERVICES** AND IDENTITY PUBLISHING MATCHING Banks & Collection Bertelsmann Insurers Agencies Leasing Corp **ID Analytics** Asabi Investigations Shimbun TransUnion Equifax MARKETING Companies in many sectors DATA DATA seamlessly gather, analyze, LexisNexis share, trade, and utilize Online Shops **Politics** Utilities Grocery Pharmacles Advocacy Education RETAIL, CONSUMER **PUBLIC SECTOR AND GOODS AND SERVICES KEY SOCIETAL DOMAINS** Law Housing Brands Order Travel & Enforcement GOVERNMENT Employment Hospitality SURVEILLANCE Healthcare

Figure 16: Companies involved in the personal data business

Source: Wolfie Christl, "Corporate surveillance in everyday life: How companies collect, combine, analyse, trade and use personal data on billions". Cracked Labs (June 2017)²³⁶.

²³⁶ Christl (2017) referenced above⁹³

Online platforms (including online marketplaces such as Amazon, social media websites such as Facebook²³⁷ or search engines and advertising platforms such as Google) also play an increasingly important role in the value chain as intermediaries, as they may not only collect personal data to personalise better their content for users, but also allow businesses to target better their products and services on the platform itself, based on users' data. For example, "data from data brokers such as Acxion, Datalogix and Epsilon was integrated in all categories of Facebook advertising [...] On top of the exchanging data with the mentioned partners, Facebook also collaborates with hundreds of other data dealers, Ad technology developers, data and marketing analysis companies, vendors, service providers and other partners that are providing technical infrastructure services"²³⁸²³⁹. The data collected is used for three main types of user targeting with ads and profiling: "basic information (location, age, gender and language), detailed targeting (based on users' demographics, interests and behaviours) and connections (based on specific kind of connection to Facebook pages, apps or events). Every user is basically profiled and tagged with the use of those three methods and is being offered as a target for advertising."²⁴⁰

At European level, the data market is evolving. According to the European Data Market study measuring the size and trends of the EU data economy²⁴¹, the European "overall data economy" (an estimate of the total value of all data-driven innovation and data technologies, measuring the direct, indirect and induced value of data in the economy) grew from 247 billion EUR in 2013 to 300 billion in 2016. Based on the measurement of various market indicators, such as data market value, number of data companies, number of companies using data etc., the study developed three possible scenarios to forecast the data market development until 2020:

- **High growth scenario** the data market's development accelerates, due to the increased adoption of data-driven technologies.
- **Baseline scenario** the data market evolves at a moderate but still strong pace, continuing the current positive growth trends.
- **Challenge scenario** lower uptake of data-driven technologies due to less favourable market conditions, resulting in slower data market growth and digital innovation²⁴².

The "European Data Market Monitoring Tool"²⁴³ projects that in terms of "market value" (the aggregate value of the *demand* of digital data, not taking into account the direct, indirect or induced value of data), between 2016 and 2020, the European data market will grow between 18% in the "Challenge" scenario and 80% in the "High growth" scenario, see figure below.

²³⁷ The current study focusses on personalised pricing/offers from online firms such as e-commerce sites, marketplaces, search engines and online sellers who may also have offline activity. Although social networks are not included in the scope of the study, Facebook plays an important role in the data ecosystem as the Facebook-owned companies share users' data with various actors on the online market such as advertisers (see footnote 97 on Facebook Data policy).

²³⁸ DataEthics (2017), Andreea M.Belu, "The Massive Data Collection by Facebook – Visualized". Available at: https://dataethics.eu/en/facebooks-data-collection-sharelab/

²³⁹ "Platforms and marketplaces are explored in more details in Section 3.2.3.

²⁴⁰ ShareLab (2017), "Facebook Algorithmic Factory 3: Qualified Lives on Discount". Available at: https://labs.rs/en/quantified-lives/

²⁴¹ IDC & Open Evidence (2017) on behalf of the European Commission, "The European Data Market Study: Final report". Available at: http://datalandscape.eu/study-reports/european-data-market-study-final-report

²⁴² European Data Market Study: Final report referenced above²⁴¹

²⁴³ The European Data Market Monitoring Tool: http://datalandscape.eu/european-data-market-monitoring-tool

Table 7: The growth of the European data market in terms of market value, data user companies and number of data companies

Indicator	2015	2016	2020 Challenge Scenario	2020 Baseline Scenario	2020 High growth
Data Market Value (in billion EUR)	54,351	59,539	70,407	79,637	106,821
Data users companies *	650 750	661 050	668 400	727 250	1 098 600
Number of Data companies **	249 100	254 850	265 250	310 250	359 050

^{*}Data user companies represent the demand side of the data market and are organisations that generate, exploit collect and analyse digital data intensively and use what they learn to improve their business.

Source: The European Data Market Monitoring Tool²⁴³

What is the market value of personal data? The *Financial Times* project "How much is your data worth?" provides an interactive calculator to estimate the prices for different personal data parameters, based on industry pricing data in the US²⁴⁴. The calculator demonstrates that the more specific the information related to the individual is, the more valuable it is to buyers²⁴⁵. The table below provides examples of the prices *per person* for specific data parameters on the data market, as calculated by the *Financial Times*:

Table 8: Prices for data parameters on individual consumer (non-exhaustive list)

Category	Data type	Price (in dollars) per person
Online searches or visited	Auto	0.0021
websites on specific topics	Political topics	0.0019
	Telecom and television purchase	0.0015
	Gaming/Food/Gossip/Education	0.0013
	Financial information/ Retail/Travel	0.0011
	Cooking topics/Social influencers	0.008
	Movie information	0.003
Consumer possession of a loyalty card	Yes	0.001
	Car	0.0018

²⁴⁴ Financial Times (FT), "How much is your data worth". Calculator to estimate the prices data brokers in the US pay for personal data. Available at: https://ig.ft.com/how-much-is-your-personal-data-worth/

^{**}Data companies are enterprises whose core business is the production and delivery of digital data-related products, services, and technologies. They represent the supply side of the data market.

²⁴⁵ Based on findings obtained through the Financial Times personal data value calculator referenced above.

Category	Data type	Price (in dollars) per person
Consumer's intention to	Other vehicles	0.0012
	Mobile phone	0.0125
buy specific products or services	Travel	0.0012
	Consumer packaged goods/ Financial products and services	0.001
	Clothes	0.0008
Activities and hobbies	Fitness/Travel/Cruise	0.03
	Participation in activities related to weight loss	0.105
	Ownership of a boat	0.076
	Ownership of a house - yes	0.092
Property	Ownership of a house combined with other data parameters (size of home, mortgage etc.)	Up to 0.112
	Birth of a child - firstborn	0.102
Major life events	Birth of a child – not a firstborn	0.087
	Trimester – second and third	0.122
	Engagement	0.10
	Recently changed residences	0.085

Source: List elaborated using the Financial Times (FT) calculator, "How much is your data worth"246

Olejnik et al (2013) confirmed that users with a known online history are valued higher on RTB ("real-time bidding", see Section 2.1) platforms²⁴⁷. Furthermore, the paper provided evidence that information from which consumers' intentions can be deduced (e.g. having looked at specific products), is sold at higher prices than "more general" browsing history.

A study conducted by Orange in 2014²⁴⁸ found that a large majority of consumers (80%) know that their personal data has a value for businesses. Consumers evaluate this fact differently, depending on the type of data and the organisation collecting it. For example, consumers value their data 20% higher when shared with an unfamiliar organisation to which they have not previously provided personal information and have not purchased from. Furthermore, consumers were found to assign higher value to data which corresponds to the profiles targeted by a specific organisation. The figure below displays examples of the prices that consumers *believe* their data is worth or should be worth, depending on their familiarity with the organisation and the information shared.

Lukasz Olejnik, Tran Minh-Dung, Claude Castelluccia. Selling Off Privacy at Auction. 2013. Available at: https://hal.inria.fr/hal-00915249/PDF/SellingOffPrivacyAtAuction.pdf

²⁴⁶ Financial Times personal data value calculator referenced above²⁴⁴

²⁴⁸ Orange (2014), « The future of digital trust: A European study on the nature of consumer trust and personal data. September 2014. Available at: https://www.orange.com/content/download/25973/582245/version/2/file/Report+-+My+Data+Value+-+Orange+Future+of+Digital+Trust+-+FINAL.pdf

Figure 17: Average amount of money that a consumer wants to receive for sharing different types of personal information

	familiar organisation	unfamiliar organisation
my full name or date of birth	£12.16	£15.22
my mobile number	£13.96	£16.20
my location (e.g. via mobile GPS tracking)	£13.35	£16.02
my annual income	£14.61	£16.50
my marital status	£9.63	£12.83
my sexual orientation	£11.38	£13.85
my job	£11.11	£13.83
my children's details (e.g. sex, age)*	£12.44	£14.53
details of my family members' preferences	£14.07	£16.21
email addresses of 5 people in close personal network	£14.46	£16.67
history of purchases made on mobile phone	£13.25	£16.31
my postal address	n/a	£15.67
my main personal email address	n/a	£15.11
average (mean)	£12.77	£15.30

Familiar organisation: entity known to the consumer from which he/she has previously purchased

Unfamiliar organisation: entity of which the consumer may have heard of, but have not purchased from or shared personal data with

Source: Orange (2014), "The future of digital trust : A European study on the nature of consumer trust and personal data" 249

However, as pointed out by CMA $(2015)^{250}$, it may be difficult for consumers to assign accurate values to their data, as firms' revenues are affected also by other factor not related to consumer data. Nonetheless, the report concludes that this further demonstrates the complexity of estimating the value of personal data.

3.2.2. Practices where online business operators transmit²⁵¹ consumer data

The literature, as well as the stakeholder consultation, suggest that many actors on the online market do **collect data for personalised pricing/offers and may transmit this data to others** (RQ4). According to the results from a survey to representatives in the marketing and retail industry released by Forbes Insights and Criteo in 2017²⁵², retailers

²⁴⁹ Orange (2014) referenced above²⁴⁸

UK Competition & Markets Authority (2015), "The commercial use of consumer data". Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/435817/The_commercial_use_of_consumer_data.pdf

²⁵¹ Sometimes referred to as share or transfer

²⁵² Forbes Insights in association with Criteo. "The Commerce Data Opportunity: How collaboration levels the retail playing field". 10 October 2017. Available at: https://www.criteo.com/news/press-releases/2017/10/criteo-and-forbes-study-commerce-data-opportunity/

and marketers are aware of the potential that data holds, as 42% believed that "customer data is a strategic resource" ²⁵³.

As noted above, the data ecosystem is complex and involves different types of actors, most of which are involved in the collection, sharing or transmitting of users' data. The complexity of the system is due to the different roles the same type of actors often play (for example, a company can collect and transmit data). Companies may perform one or more of the following practices: collecting data, transmitting data, allowing other parties access to company's datasets and using personalisation solutions/services of other companies instead of collecting and analysing data themselves.

In terms of obtaining data, third parties such as advertising providers may acquire (or "buy", as described in the source) data from marketing companies or data aggregators²⁵⁴. Marketers may also collect subscribers' data from media organisations or digital publishers²⁵⁵ and transmit data to advertising providers and retailers. Another report²⁵⁶ also suggests that companies such as large clothing retailers buy data from third parties and data brokers to optimise their marketing strategies. On the other hand, retailers may be vendors as well. For example, retailers also sell aggregated consumer purchase data to market research companies and consumer data brokers²⁵⁷. In other cases, retailers may combine data collected with additional data already acquired from aggregators²⁵⁸.

In addition, e-commerce platforms often use the services of specialised companies such as data brokers, data analytics or personalisation companies. Experts consulted for this study (7 out of 10) noted that transmitting data from third parties through data aggregators and (especially for advertisers) through real-time bidding platforms is a common practice for e-commerce websites (please see Section 2.1 on advertising practices). Other companies such as marketing agencies collect or buy cookie IDs to consequently create user profiles. In addition, price comparison tools often trade the data collected by their websites to advertisers. The table below illustrates the different roles companies are playing on the data market, depending on the circumstances (non-exhaustive list).

Figure 18: Examples of the different roles the actors on the market play

Entities transmitting data	Entities acquiring data from other companies			
Data brokers	Advertising companies			
	 Industries (retailers, travel, financial services, insurance) 			
	Online platforms			
	 Advertisers 			
	E-commerce websites and retailers			
Marketing agencies	Advertising companies			
	E-commerce websites and retailers			

²⁵³ The survey was conducted in France, Germany, Japan, the United Kingdom and the United States.

²⁵⁶ UK Competition & Markets Authority (CMA). The commercial use of consumer data. Report. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/435817/The_commercial_use_of_consumer_data.pdf

²⁵⁴ Bujlow et al referenced above¹⁴⁵

²⁵⁵ Christl (2017)⁹³

²⁵⁷ Christl (2017)⁹³

²⁵⁸ Charles Duhigg, New York Times. How companies learn your secrets. 16 February 2012. Available at: http://www.nytimes.com/2012/02/19/magazine/shopping-habits.html

Media Organisations/digital publishers	Marketing agencies		
	Third party data providers		
E-commerce websites and retailers	Marketing agencies		
	Data brokers		
Price comparison tools	Advertising companies		
Third party data providers	Data brokers		
	Advertising companies		
	Marketing agencies		
	E-commerce websites and retailers		

It is important to explain the key role of data brokers in the collection and transmitting of consumers' personal data²⁵⁹. The biggest data brokers are American, however they have a presence worldwide (e.g. Acxiom, Experian)²⁶⁰. As noted above, data brokers may collect the data themselves or may procure it from commercial, governmental and public sources. This can include data about the user's name, address (changes), demographic attributes, phone connections, credit card details, occupation, education, purchases, property ownership, income, interests, and ethnicity, as well as religious and political affiliation (see figures below).²⁶¹ As an example, national postal services play a central role in the consumer data business selling information on peoples' addresses²⁶².

The below graphs provide an illustration of the complex interactions of different actors in the data ecosystem. In this example Acxiom is the data broker, which provides other data brokers (Oracle in the case below) access to its consumer database. In addition to acquiring and transmitting data, data brokers provide software to manage their clients' customer databases, enhance data, merge lists, remove duplicate records, and to sort them into groups with specific characteristics. Some of them have introduced the so called "master customer databases" as single sources for information on individuals and households, in which every person gets a unique code allowing them to link together records from different sources by combining key identifiers such as names, addresses, and zip codes and so forth. In Europe, data brokers rely more on aggregated data to profile individuals, due to EU data protection regulations.

The clients of data brokers use their services to manage their customer databases as well as to analyse, segment and sort customers based on their characteristics, behaviour, profitability and lifetime value. As an example, information about a person's registered vehicle can be used as an indicator of the person's social standing, purchasing power and attitudes²⁶³. In addition, client companies can collect consumer data and append it to their own data. The leading global data brokers manage several thousands of customer databases, totalling up to billions of individual end-client records. Acxiom's clients include 47 of the Fortune 100 companies in different sectors such as direct marketing, retail, consumer packaged goods, technology, travel, financial services etc.²⁶⁴.

²⁵⁹ Datatilsynet (2015)⁵⁸

²⁶⁰ Datatilsynet (2015)⁵⁸

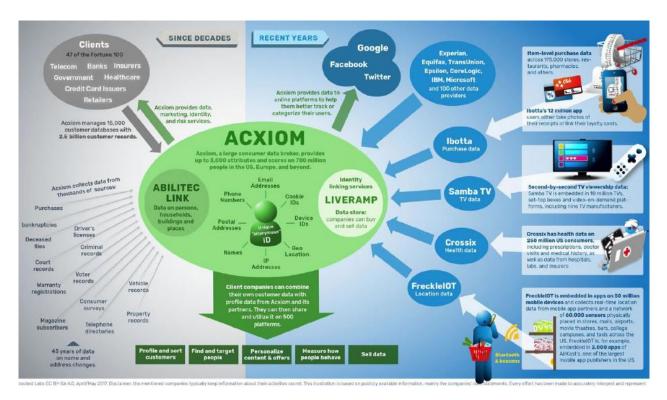
²⁶¹ FTC (2014): Data Brokers

 $^{^{262}\} http://www.sueddeutsche.de/wirtschaft/verbraucherschutz-kritik-am-daten-handel-der-post-1.196084$

²⁶³ Forrester (2015): The Forrester Wave™: Customer Insights Services Providers

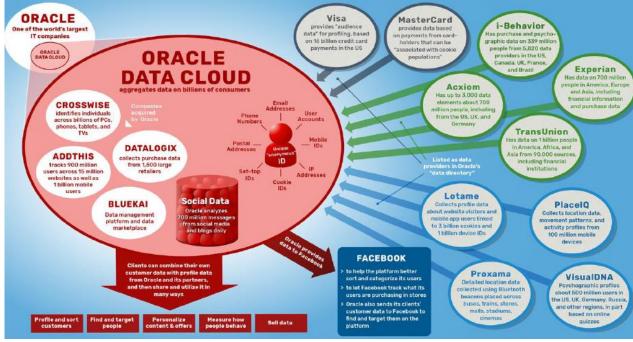
²⁶⁴Acxiom 2016 Annual report: https://s21.q4cdn.com/580938034/files/doc_financials/annual_reports/ACXM_Annual_Report_FINAL_RRD_Printers_Proof_6-17-16_.pdf

Figure 19: Example of Acxiom's data providers, partners and clients



Source: Wolfie Christl (2017). Corporate surveillance in everyday life: How companies collect, combine, analyse, trade, and use personal data on billions²⁶⁵.

Figure 20: Example of Oracle's data providers, partners and clients



Source: Wolfie Christl (2017). Corporate surveillance in everyday life: How companies collect, combine, analyse, trade, and use personal data on billions²⁶⁶.

²⁶⁵ Christl (2017)93</sup>

²⁶⁶ Christl (2017)93</sup>

Examples of data brokers on the European market include French company **Dawex**²⁶⁷, which offers a secure data platform for monetising or exchanging data between different parties, or **qDatum**^{268, 269}. Retail e-commerce businesses can use the services of data companies to collect rich data about consumers, add additional information on them, and utilise the enriched digital profiles across a wide range of technology platforms.

The data market monitoring tool of the European Commission provides further insights into the firms at EU-level that provide for example analytics, personalisation, and/or data collection services²⁷⁰. For instance, data science company **HeyStacks**²⁷¹ provides personalised targeting solutions and intent profiling of consumers for companies (predicting consumers' intentions) based on users' browsing activities and contextual data (e.g. time, location). Another example is Swedish company **Tajitsu**²⁷², which offers predictive analytics, real-time recommendations and personalising offers for consumers. The Spanish firm **Konodrac**²⁷³ offers various services, based on predictive analytics to companies for customer segmentation, personalised recommendations, digital marketing and ecommerce. **Findify**²⁷⁴ offers search engine and navigation optimisation for ecommerce websites. Other examples of personalisation and profiling companies include **Tapoi**²⁷⁵ or **Criteo**²⁷⁶.

The online data market: findings from the stakeholder survey

In the stakeholder survey for this study, the majority of DPA respondents (7 out of 13) reported that companies use a combination of methods to obtain consumer data: they either collect the data themselves through tracking technologies (e.g. cookies, fingerprinting) and/or via social media and websites' online identification forms, or they obtain it from third parties (e.g. data brokers and aggregators) ²⁷⁷. Less than half of stakeholders consulted reported to be aware of practices where business operators actually obtain consumer profiles from other companies, while most respondents were not aware of such practices in their country.

Concerning the practice of transmitting consumer data²⁷⁸, out of 12 DPA respondents, 5 suggested that there are business operators who transmit consumers' personal data to third parties. One of these respondents specified that often data is transmitted by companies which provide data to platforms for airline ticket selling/displaying, or within the same group of associated companies that transmit collected data to their daughter companies. The majority of (7 of the 12) DPA respondents, reported to have no particular experience or to be aware explicitly of such practices in their country. **National experts highlighted that the practices of transmission of personal data are not as widespread in the EU compared to the US resulting from the application of the EU data protection legislation.**

The majority of business operators did not/could not confirm that e-commerce websites acquire actual consumer profiles. Considering this, it should be noted that companies are

²⁶⁷ https://www.dawex.com/en/

²⁶⁸ https://www.qdatum.io/

For more details, please refer to the EU data market monitoring tool website: http://datalandscape.eu/companies

European Data Market Monitoring tool: http://datalandscape.eu/companies?f%5B0%5D=field_action_area%3A2

Please note that the list of companies may expand as new companies are added to the map.

²⁷¹ https://www.heystaks.com/about-us/

²⁷² http://tajitsu.com/

²⁷³ http://www.konodrac.com/en/business/

²⁷⁴ https://findify.io/

²⁷⁵ http://www.u-hopper.com/portal/site/products

²⁷⁶ https://www.criteo.com/

²⁷⁷ Q9, Survey to DPAs: "To your knowledge, how exactly do online business operators collect the information needed in order to provide personalised practices to citizens? Do they do it themselves (if so, how exactly) or do they procure it from other companies that specialise in such practices?"

²⁷⁸ Q13, Survey to DPAs: "Do online business operators who collect personal data for personalised pricing/offers transmit consumer data/profiles to third parties?"

generally reluctant to share such information due to the negative perception of these practices. From the 9 respondents who replied to the question²⁷⁹, 5 were either not aware or did not think that their competitors obtain actual consumer profiles from other companies which specialise in data collection. Another 4 respondents specified that companies often prefer to employ personalisation solutions or services to perform the profiling and personalisation on their behalf, rather than acquiring the consumer data itself. Three out of these 4 respondents mentioned that their business model is based on privacy-by-design and they do not transmit the consumer data they collect.

Similarly, the majority of business operators did not/could not provide a definitive answer to the question on how frequently online business operators obtain or transmit consumer data/profiles in the EU28²⁸⁰ ²⁸¹. Only 1 respondent deemed this practice to be occurring 'very frequently'. Another respondent mentioned that this could happen 'occasionally'. According to 3 respondents, on the other hand, this is a rare practice or never occurs. Three interviewed business operators suggested that the acquiring and transmitting of data is a practice more common in the US, although they did add that there are companies who are involved in such practices in Europe as well.

The findings from the stakeholder consultation make it clear that there are various actors involved in the collection and transmission of consumers' data. Furthermore, the roles of the different actors as entities acquiring and transmitting data are often blurred with many companies having dual functions in the market. In addition, consulted stakeholders appeared to have low knowledge on the exact mechanisms of data transmitting, making it difficult to even attempt to quantify the prevalence of these practices.

Overall, the evidence collected suggests that companies may not directly collect/acquire and process data/profiles, but instead they tend to use other companies who offer personalisation or analytics solutions. Many companies also choose to outsource the data collection, analytics or personalisation services to third parties due to lack of resources²⁸². They may also allow data brokers' access to their customer databases in order to combine the existing data with additional information from the data broker's own database. There is little interest of companies to share insights in their business models with regards to usage, sharing, transmitting or acquiring of data adding to the low transparency of the data ecosystem as a whole. In addition, there is generally little knowledge among the wider public or authorities about the exact interplay of such practices.

3.2.3. The transmission of consumer data on online marketplaces

In order to understand the transmission of consumer data in relation to online marketplaces (RQ5), it was first necessary to have a look at the generic role of platforms in the online market.

The European Commission's Communication on online platforms²⁸³ noted that: "Online platforms come in various shapes and sizes and continue to evolve at a pace not seen in any other sector of the economy. Presently, they cover a wide-ranging set of activities including [...] online advertising platforms, marketplaces, search engines, social media and

²⁷⁹ Q11, Business Operators Survey to Ecommerce websites: "Are you aware of practices in your country or within the EU28 where your competitors buy consumer profiles from other companies, which specialise in data collection (e.g. data brokers)?"

²⁸⁰ Q13 and Q11 in relation to acquiring consumer data/profiles, Business Operators Survey to Ecommerce websites and to Technology companies offering online personalisation solutions, respectively.

²⁸¹ Q14 and Q12, in relation to **transmitting** consumer data/profiles to third parties, Business Operators Survey to Ecommerce websites and to Technology companies offering online personalisation solutions respectively
²⁸² CMA report referenced above²⁵⁶

²⁸³ Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions on online platforms and the Digital Single Market opportunities and challenges for Europe. COM(2016) 288 Final. Available at: http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52016DC0288#

creative content outlets, application distribution platforms, communications services, payment systems, and platforms for the collaborative economy."²⁸⁴ An OECD report on big data (2016) defines platforms as "the main interface between consumers and other marketplaces"²⁸⁵. These platforms have extensive data on consumers and participants, collected from online transactions, loyalty schemes, forms submitted by users which they sometimes use to offer price discounts or free products in exchange²⁸⁶. An online marketplace on the other hand is a website or an app which facilitates B2C sales between various third party sellers and consumers.

A global survey on platforms' business models conducted by the Center for Global Enterprise in 2016 provides another typology and categorises companies such as Google or Alibaba as "integrated platforms" – combining features from transaction platforms, which facilitate double-sided markets, and integrated platforms characterised with an extensive third party network²⁸⁷. These large platforms operate multiple sub-platforms, hence they represent "platform conglomerates"²⁸⁸. E-commerce is the largest sector by number of platform and the second largest by market value, according to the survey's results²⁸⁹. Such marketplaces often act as a platform for advertisers and often receive a share of the advertising revenues²⁹⁰. One of the biggest of such platforms is Amazon', whose online advert revenues are growing faster than other larger advert publishers – the company saw a 48.2% increase in advert revenues in 2017 and is ranked the 4th advert display company with 3% of the total net US digital display advert revenues²⁹¹.

There are various forms of online marketplaces where the transmission of consumer data may occur. Data can be transmitted not only on B2C platforms and marketplaces, but also on B2B platforms between different market players (e.g. advertisers, marketers, retailers or other platforms) such as data marketplaces. These types of marketplaces (and platforms) are explored below.

The transmission or sharing of consumer data on B2C online marketplaces

Online marketplaces provide their partner companies, the online sellers of goods or services, with a series of services. The list below provides an indication of the services offered to sellers by different leading marketplaces:

- Increasing the visibility of sellers' products (in addition to their own products) by providing access to a large central platform frequently used by a large variety of individual customers through various channels (desktop, mobile).
- Access to multiple national/regional marketplaces across Europe through one entry point. For example, Amazon provides optional access to all 5 marketplaces in the UK, Germany, France, Italy and Spain through each individual portal.
- Providing key metrics on sellers' product listings, see below for an example from eBay.

²⁸⁴ COM(2016) 288 Final

²⁸⁵ OECD (2016a)¹⁸²

²⁸⁶ OECD (2016a)¹⁸²

²⁸⁷ Peter C. Evans, Annabelle Gawer, The Center for Global Enterprise, "The Rise of the Platform Enterprise: A Global Survey". The Emerging Platform Economy Series No.1. Available: https://www.thecge.net/app/uploads/2016/01/PDF-WEB-Platform-Survey 01 12.pdf

²⁸⁸ The Center for Global Enterprise survey report referenced above²⁸⁷

²⁸⁹ The Center for Global Enterprise survey report referenced above²⁸⁷

²⁹⁰ OECD (2016a)182

Emarketer, "Understanding Amazon as an Advertising Platform: Amazon will earn \$1.65 billion in net US digital ad revenues this year". 26 October 2017. Available at: https://www.emarketer.com/Article/Understanding-Amazon-Advertising-Platform/1016672

- Managing the sellers' inventory and listings through dashboards, see below for an example by Amazon²⁹².
- Payment services to facilitate the payment process for sellers, including tools for invoicing, payment processing, payment collection, and refund management.
- VAT services including VAT registration and filing for one or several countries for cross-border sellers.
- Managing orders, stocks, shipping and track packages.
- Running promotions to customers to promote a brand or particular products based on key word searches provided by the customer. Sellers pay for promotions on a Cost-per-Click basis²⁹³.
- Support for sellers to cope with the platform and optimize sales through call centres, seller fora, market research papers, webinars and presentations.
- Specialized support for "sizing" of clothes dedicated to clothing sellers.
- Providing analytics capacities on various data sets through 3rd party plug-in software such as:
 - Customer feedback
 - Research market prices through data of competing sellers
 - Accounting support
 - o Customer management and communication, e.g.
 - Customer profiles with order metrics
 - Customer location heatmaps
 - Customer and Campaign management
 - Automatic personalised eBay messages after order events (e.g. marked dispatched)
 - Automatic personalised feedback reminder messages
 - View activity logs showing sent messages, feedback left and feedback received
 - Immediate notifications if negative or neutral feedback is received
 - Customer online purchase inventory
 - Data visualisation
 - Profit calculation

²⁹² http://g-ec2.images-amazon.com/images/G/02/Webinar/Selling-in-Europe-with-Amazon.pdf?ld=AZUKGNOSellC

²⁹³Amazon Webinar on increasing sales with promotions and sponsored products: http://g-ec2.images-amazon.com/images/G/02/Webinar/Recordings/20140320IncreaseYourSaleswithPromotionsandSponsoredProductsWebinar._V341730804_.mp4?Id=AZUKGNOSelIC

Whether data is transmitted to other parties or sellers depends on the platform, but according to our research it does not seem to be a major service put forward to sellers. Online marketplaces are most likely to use the data they have for their own benefit, i.e. to increase the volume of transactions as transaction fees are one of their main sources of income, rather than make them available to the sellers on the marketplace. Some companies admit that they do not transmit data to third parties. For example, Amazon allegedly does not allow access to consumer data to sellers on its marketplace in order to retain a competitive advantage²⁹⁴ ²⁹⁵. Marketplaces usually receive a commission for each product sold through the platform (or they actually sell their own products themselves) and provide other additional services directly or through indirect service providers for a fee.

Figure 21: Examples of the services provided by eBay (top) and Amazon (bottom) to sellers on their marketplaces

Review key metrics

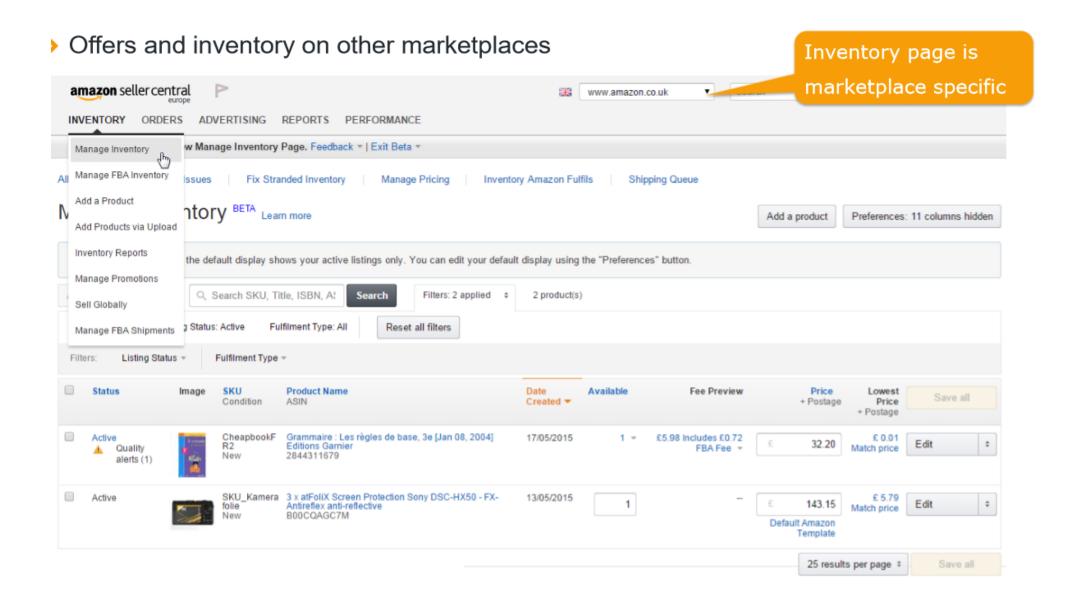
On the same line as each listing, you'll see key metrics that tell you how the listing is doing.

- Rank Rank is the search placement of your listing with respect to other listings. For example, a listing that ranks 5th place is more visible than a listing that ranks 37th place. The rank is the result of a search using the keywords that you entered in the listing analytics search box. Buyers may use different search words.
- Format Format describes whether an item is offered through an auctionstyle listing or a fixed price listing.
- Impressions Impressions are the number of times your listing appears to potential buyers in a search.
- Clicks Clicks are the number of times buyers clicked on your listing in search to view your listing.
- Click through Click through is the number of clicks divided by the number of impressions. A higher click through rate is better, meaning members were more likely to click on your item when they saw it in a search
- Sold items Sold items are the number of times buyers purchased an item from your listing. This number will only be greater than one when your listing is a multiple quantity fixed price listing.
- Sell through Sell through is the number of items that sold divided by the number of clicks for your listing. A higher sell through rate is better, meaning members were more likely to buy your item when they clicked to view your listing.
- Watchers Watchers are the total number of members watching your listing.
- Sales Sales is the dollar value of items sold in a listing.

Source: http://pages.ebay.com/help/sell/listing-analytics.html (above) and https://sellercentral.amazon.com (below)

²⁹⁴ The Guardian, "Third party sellers and Amazon – a double-edged sword in e-commerce. 23 June 2015. Available at: https://www.theguardian.com/technology/2015/jun/23/amazon-marketplace-third-party-seller-faustian-pact

²⁹⁵ https://www.amazon.co.uk/gp/help/customer/display.html/ref=footer_privacy?ie=UTF8&nodeId=502584



Another possible way marketplaces are sharing data is through partnerships with retailers in order to combine the companies' data resources (e.g. Alibaba and PepsiCo strategic agreement)²⁹⁶. A study conducted in 2013 showed that the US retail chain Walmart shared online consumer data with over 50 third parties, such as data brokers or online advertising companies²⁹⁷. However, the company itself has stated that "third-party companies do not have access to any identifiable customer data"²⁹⁸. On the other hand, Walmart entered into partnership with Google in order to enable voice-ordered purchases by combining Google's virtual assistants with the retailer's consumer purchase history data²⁹⁹. Although it is not yet clear how customer data will be used or shared in the context of this partnership, this is an indication of the importance of "data collaboration" in the retail online sector³⁰⁰.

In terms of financial services marketplaces, fund supermarkets and online brokers are of particular interest as they are increasing their market share substantially and provide access to a large variety of investment products, such as investment funds, ETFs, complex products like derivatives as well as other products that are common in the respective countries, e.g. life insurance products in France or Individual Savings Accounts in the UK. The services of these platforms are usually limited to one country and are most developed in the UK and Germany. Providers of financial products connect to the platforms and provide all the relevant information on share classes, risk class, performance, costs etc. Depending on the financial products, the platform receives a commission or a fee from the product manufacturer and/or requires the final individual investor to pay a recurring annual fee for the management of his account. As fund supermarkets and online brokers provide access to several hundreds or even thousands of financial products, they usually provide different elements of information and guidance that help the retail investor choose products that are (or appear to be) suitable.

Consumers are also increasingly relying on comparison tools (websites, apps) to compare products and services according to their prices, quality or other parameters. Usually comparison tools rely on a twofold remuneration model. On the one hand they are paid on a Cost-per-Click basis when the customer clicks on a certain product and is directed towards the website of the seller. On the other hand, they allow online sellers to launch promotions and special offers on the comparator webpage as well as by sending targeted emails to consumers.

The transmission of consumer data on online marketplaces: the stakeholder feedback

Regarding the type of information transmitted and the transparency of the online marketplaces vis-à-vis consumers, none of the 10 national experts could provide a definitive answer on the specific type of information transmitted, as it generally could include any type of data. Three experts mentioned that online marketplaces are often not transparent about these practices. Only 2 out of the 10 companies who replied to the business operators survey indicated to have made use of an online marketplace to sell their products. These two companies noted that they are either not aware or do not think that consumer data/profiles at the disposal of these marketplaces are transmitted to the seller on the marketplace.

²⁹⁷ The Center for Media Justice, ColorOfChange & Sum of Us, "Consumers, big data and online tracking in the retail industry". November 2013. Available at: http://centerformediajustice.org/wp-content/uploads/2014/06/WALMART_PRIVACY_.pdf

²⁹⁶ Forbes, "Here's How Alibaba is Leveraging Its Data". 16 May 2017. Available at https://www.forbes.com/sites/greatspeculations/2017/05/16/heres-how-alibaba-is-leveraging-its-data/#4cf71f233292

²⁹⁸ The Wall Street Journal (WSJ). "Data Fusion, Data Privacy: What we can learn from Walmart's Flexible Data Architecture". 31 March 2017. Available at: https://www.forbes.com/sites/danwoods/2017/03/31/data-fusion-data-privacy-what-we-can-learn-from-walmarts-flexible-data-architecture/3/#46a2ab682b25

²⁹⁹ The Wall Street Journal (WSJ). "Wal-Mart and Google team up to challenge Amazon". Available at: https://www.wsj.com/articles/wal-mart-and-google-partner-to-challenge-amazon-1503460861

³⁰⁰ Criteo, "Amazon goes offline, Walmart goes online: why data & collaboration matter". 17 October 2017. Available at: https://www.criteo.com/insights/amazon-goes-offline/

The national experts interviewed suggested that it is likely that consumer data at the disposal of online marketplaces is transmitted to other sellers on the marketplace/interested parties (those can include a variety of actors on the online data market such as advertisers, social networks etc.)³⁰¹. One expert specifically mentioned that online marketplaces and platforms are not usually disclosing this type of information. However, the interviewed experts also noted that such practices are more difficult in the EU compared to the US, where the data protection regulatory framework is different.

It is also important to note that the limited information available may be due to the fact that at EU level most of retailers do not use a marketplace to sell their products. For example, a European Commission-led inquiry on the e-commerce sector found that 90% of respondents (out of 1051 responses in total) prefer to use their own online shop when selling online 302 . Only 31% of respondents sell both via their own online shop and a marketplace and even less answered that they sell only via a marketplace (4%) 303 . However, there are Member States where retailers use marketplaces more often – Germany (62%), United Kingdom (43%) and Poland (36%) 304 . The survey also found that smaller retailers tend to see more benefits in selling via a marketplace and do so more often than large retailers.

Transmission or sharing/acquiring of consumer data on B2B data platforms

In addition to B2C marketplaces such as the ones discussed above, there are **B2B platforms** which enable retailers, advertisers and other market players to transmit data (explored below).

Data management platforms (DMPs) are one way companies exchange information with. Big data platform BlueKai (acquired by Oracle in 2014)³⁰⁵, provides the following definition: "A DMP is a centralized data management platform that allows you to create target audiences based on a combination of in-depth first-party and third-party audience data; and to accurately target campaigns to these audiences across third-party advert networks and exchanges [etc]"306. DMPs are widely used by advertising and marketing companies for the personalisation or targeted advertising - according to Gartner, 50% of today's enterprises use such platforms³⁰⁷. The platforms import customer data from various channels and sources, match different parameters with customer IDs, perform additional data collection to enrich datasets and allow companies to access data vendors³⁰⁸. DMPs differ from customer data platforms (CDPs) in their limited ability to build more persistent customer profiles, as the latter allow to better synchronise customer online and offline sources and rely less on third-party data³⁰⁹. An example is Adobe's data management platform (DMP) "Audience Manager" ³¹⁰ announced in 2016, on which

³⁰¹ Q11, Survey to National experts: "In the case where business operators make use of online marketplaces to sell products, is consumer data at the disposal of the online marketplace shared/transferred/sold, partially or entirely, to the sellers on that marketplace?"

Report from the Commission to the Council and the European Parliament: Final report on the E-commerce Sector Inquiry. Brussels, 10.5.2017. Available at:

http://ec.europa.eu/competition/antitrust/sector_inquiry_final_report_en.pdf ³⁰³ E-commerce Sector Inquiry referenced above³⁰²

³⁰⁴ E-commerce Sector Inquiry referenced above³⁰²

³⁰⁵ https://www.oracle.com/corporate/acquisitions/bluekai/index.html

³⁰⁶ BlueKai, "Data Management Platforms demystified". Whitepaper. Available at: http://www.bluekai.com/files/DMP Demystified Whitepaper BlueKai.pdf

³⁰⁷ Smarter with Gartner series, "Do you need a data management platform". Available at: https://www.gartner.com/smarterwithgartner/do-you-need-a-data-management-platform/

Martin Kihn, Garner, "What does a data management platform do, anyway?" 07 January 2015. Available at: https://blogs.gartner.com/martin-kihn/data-management-platform/

³⁰⁹ Gartner for Marketers, "CDP: Another three letter ancronym marketers need to know". 11 February 2017. Available at: https://blogs.gartner.com/simon-yates/2017/02/11/cdp-another-three-letter-acronym-marketers-need-to-know/

³¹⁰ Adobe Digital Marketing Blog Europe, "Data: The Emergence of Marketplaces". Available at: https://blogs.adobe.com/digitaleurope/digital-marketing/data-the-emergence-of-marketplaces/

advertisers and content publishers subscribe to "data feeds" and can buy, sell or exchange easily data as long as they use the same DMP³¹¹.

Another way for companies to access quality data is through "data cooperatives" platforms. These platforms represent "pooled data assets" which allow retailers, especially smaller ones, to gain a competitive advantage through access to large amount of data and counter the market dominance of other retail giants. According to the Forbes Insights & Criteo survey results, three-fifths of the brands and retailers reported to be a part of data cooperatives³¹².

An example of such a system in the EU is the "Commerce Marketing Ecosystem" announced by French Ad tech company Criteo³¹³ in July 2017 (currently in development), on which retailers can share and access cross-device anonymised customer data such as email addresses, and acquire (i.e. "purchase") data and information gathered from retailers physical stores, websites and apps³¹⁴. This pooling and sharing platform should help retailers to segment customers more accurately and target them better, based on the larger pool of data and information on potential customers and their shopping habits³¹⁵. This initiative comes as a response to large online marketplaces' (such as Amazon) market dominance in the retail sector and the vast amount of data at their disposal.

It has also been reported that retailers and marketers make use of **customer data platforms (CDPs)**, acting as centralised "data hubs" which integrate consumers' data from a variety of sources (e.g. emails, websites, e-commerce platforms and information as well as point-of-sale (POS) systems) and allow access to unified profiles³¹⁶.

The literature review and stakeholder consultation did not provide decisive evidence of online B2C marketplaces sharing/transmitting data to sellers making use of these platforms and other parties, in particular because marketplaces do not make this type of information available. On the other hand, the findings do show that specialised B2B platforms for transmitting/acquiring or sharing data between different market players do exist, especially for targeted advertising, and that new forms of data sharing are now appearing.

3.3. The transparency of online firms using personalisation techniques about data collection methods and subsequent use of consumers' personal data and their compliance with existing EU legislations

Personalisation practices might lead to transparency issues related to the way online retailers inform consumers of their data collection and data usage practices and to possibly unfair commercial practices. This section aims to assess to what extent online firms are aware of and comply with the requirements of the relevant EU and national legislation and focusses on the following research questions:

- Are companies using these techniques transparent their data collection methods and the (further/subsequent) use of consumers' personal data? (RQ4);
- Are businesses which monitor consumers' online behaviour and use this information to offer personalised prices/offers complying with consumer laws and the existing EU regulatory framework? (RQ6).

³¹¹ https://marketing.adobe.com/resources/help/en_US/aam/c_marketplace_about.html

³¹² Forbes Insights & Criteo report referenced above²⁵²

³¹³ https://www.criteo.com/

The Wall Street Journal (WSJ), "Ad tech firm Criteo to launch data cooperative to help retailers take on Amazon". 27 July 2017. Available at: https://www.wsj.com/articles/ad-tech-firm-criteo-to-launch-data-cooperative-to-help-retailers-take-on-amazon-1501163625

WSJ referenced above³¹⁴
 Forbes Technology Council, "Customer Data Platforms: The next marketing advantage". Available at: https://www.forbes.com/sites/forbestechcouncil/2017/11/02/customer-data-platforms-the-next-marketing-advantage/#148d637b3cfc

This sub-section contains the following sections:

- Brief overview of the relevant EU legal framework related to consumer and data protection and transparency requirements for online companies towards consumers (3.3.1);
- Online firms' transparency about personalisation practices in relation to transparency and related consumer concerns (3.3.2); and
- Compliance of online business operators with the EU data protection and consumer protection legal framework (3.3.3).

3.3.1. Relevant EU legal framework

This section provides an overview of the applicable EU legal framework in relation to transparency of online companies towards consumers and the cases when personalisation practices are considered unfair commercial practices (for a more detailed legal review please refer to Annex 2). More specifically, the section focuses on the following pieces of legislation:

- Unfair Commercial Practices Directive (UCPD);
- General Data Protection Regulation (GDPR); and
- ePrivacy Directive

These are presented below.

Unfair Commercial Practices Directive

The **Unfair Commercial Practices Directive 2005/29/EC**³¹⁷ **(UCPD)** applies to B2C relationships and prohibits all unfair commercial practices (Article 5). In Article 2(d), the UCPD defines B2C commercial practices as "any act, omission, course of conduct or representation, commercial communication including advertising and marketing, by a trader, directly connected with the promotion, sale or supply of a product to consumers".

Furthermore, it also prohibits misleading statements and misleading omissions, concerning prices of goods and services. The following provisions make clear that traders must be transparent about the prices charged and how these are calculated:

- Article 6 (d) on misleading statements about the price and / or the manner in which the price is calculated, and /or the existence of a specific price advantage; and
- Article 7 (4) (c) on misleading omissions- the trader must give information about the price inclusive of any taxes, or if the nature if the product is as such that the price cannot reasonably be calculated in advance, the manner in which the price is calculated.

While price discrimination and individualised, personalised pricing and behavioural profiling are not prohibited per se under the UCPD, under specific circumstances they might amount to a breach of the above-mentioned provisions. The **Guidance on the implementation/application of Directive 2005/29/EC on Unfair Commercial Practices**"³¹⁸ provides further clarifications regarding **dynamic pricing and price discrimination** and the cases when such practices might be considered unfair. In Articles 6(1)(d) and 7(4)(c) of the UCPD, it is stated that "Under the UCPD, traders can freely determine the prices they charge for their products as long as they adequately inform consumers about total costs and how they are calculated. However, in some circumstances,

³¹⁷ Directive 2005/29/EC of the European Parliament and of the Council of 11 May 2015 concerning unfair business-to-consumer commercial practices in the internal market. Available at: http://eur-lex.europa.eu /LexUriServ/LexUriServ.do?uri=OJ:L:2005:149:0022:0039:EN:PDF

Silvation (2016), "Guidance on the implementation/application of Directive 2005/29/EC on unfair commercial practices". Available at: http://ec.europa.eu/justice/consumermarketing/files/ucp_guidance_en.pdf

dynamic pricing practices could meet the definition of 'unfair' under the UCPD."³¹⁹ The Guidance further provides the following example: "A dynamic pricing practice where a trader raises the price for a product after a consumer has put it in his digital shopping cart could be considered a misleading action under Article 6(1) (d) UCPD"³²⁰. In relation to personalised pricing, traders are also free to determine their prices, provided that consumers are informed about the prices and how they are calculated.

The figures below illustrate a few examples of misleading statements/advertising related to the availability of (online) goods and services (Figure 22) and personalised pricing/marketing methods (Figure 23) that are considered as an unfair practice under the UCPD, as included in the Guidance:

Figure 22: Examples of misleading statements related to the availability of (online) goods and services and pricing/marketing methods

Misleading statements about limited availability of a product may be in breach of Article 6(1)(b) of the UCPD.

For example:

- A major accommodation booking platform was fined by the Commercial Court of Paris for displaying misleading information on the availability of accommodation and the existence of price promotions.²⁸⁹
- In April 2014, the Dutch Advertising Code Committee found advertisements on a major accommodation booking platform to be misleading. The claims were: 'We have only 1 room left!' and 'Only 1 room left' at a specific price. The authority found that it was not clear to the average consumer that these claims only related to the rooms a hotel had made available through that platform. The platform's failure to inform consumers that its claims related to those rooms only meant that consumers could be misled into believing that the hotels were fully booked, whereas in fact the same hotels could have rooms available through other booking channels. In July 2014, this decision was upheld by the Appeals Board.²⁹⁰
- A comparison tool may use different techniques to imply to consumers that a
 product is not available. For example, by using the technique of "dimming", a
 comparison tool takes down pictures related to the offer of one specific provider
 while keeping the pictures of other providers. This could lead consumers to click
 much less frequently on the offer without pictures. If such a presentation is likely
 to deceive consumers, it could be contrary to Article 6(1)(b) as misleading in
 relation to the availability of a product and to Article 7(2) UCPD as information
 provided in an unclear manner.

Source: European Commission (2016), "Guidance on the implementation/application of Directive 2005/29/EC on Unfair Commercial Practices"

³¹⁹ Directive 2005/29/EC of the European Parliament and of the Council of 11 May 2015 concerning unfair business ³²⁰ Guidance on the implementation of the UCPD referenced above.

Figure 23: Examples of misleading statements related to the availability of (online) goods and services and pricing/marketing methods

Personalised pricing/marketing could be combined with unfair commercial practices in breach of the UCPD.

For example:

• If the information gathered through profiling is used to exert undue influence e.g. a trader finds out that the consumer is running out of time to buy a flight ticket and falsely claims that only a few tickets are left available. This could be in breach of Article 6(1)(a) and Annex I No 7 UCPD.

Source: European Commission (2016), "Guidance on the implementation/application of Directive 2005/29/EC on Unfair Commercial Practices"

Personalised pricing may be based on tracking technologies that entail the storing of information, or the gaining of access to information already stored in the terminal equipment. Article 5 (3) of the ePrivacy Directive provides that storing or accessing data on users' terminal equipment shall only be allowed upon the user's consent, having been provided with clear and comprehensive information, in accordance with Directive 95/46/EC (to be replaced by the General Data Protection Regulation as of 25 May 2018). The UCPD guidance goes further to explain that the mentioning of 'material' in Article 7.5 also covers the information requirements for the processing of personal data, which must be provided to the consumers. As the document states, "if the trader does not inform a consumer that the data he is required to provide to the trader in order to access the service will be used for commercial purposes, this could be considered a misleading omission of material information". Market operators are obliged "to identify the commercial intent of the commercial practice if not already apparent from the context"³²¹ (Article 7.2). Certain forms of differential or discriminatory pricing may therefore be in breach of the Unfair Commercial Practices Directive.

The General Data Protection Regulation (GDPR)

Recital 39 of the GDPR³²² states in relation to transparency that: "Any processing of personal data should be lawful and fair. It should be transparent to natural persons that personal data concerning them are collected, used, consulted or otherwise processed and to what extent the personal data are or will be processed. The principle of transparency requires that any information and communication relating to the processing of those personal data be easily accessible and easy to understand, and that clear and plain language be used"³²³. The recital further clarifies which information the data controller is required to provide to data subjects prior to personal data processing such as the identity of the controller, the purposes for processing and its legal basis, the recipients of the data, the data retention period and the data subject's rights to be informed of the processing of such data and their right to withdraw consent at any time.

In addition, Recital 58³²⁴ recommends that this information is also provided in electronic form "when addressed to the public, through a website" due to the "proliferation of actors and the technological complexity of practice [making] it difficult for the data subject to

³²¹ Directive 2005/29/EC referenced above.

³²² GDPR referenced above 90

³²³ Idem⁹⁰

³²⁴ Idem⁹⁰

know and understand whether, by whom and for what purpose personal data relating to him or her are being collected, such as in the case of online advertising."³²⁵

Moreover, Article 22 of the GDPR on the right not to be subject to decision-making based on automated processing, including profiling, is also relevant to the scope of the study. In a context of increasingly digitised and automated processes, it captures future implications of new technologies such as the Internet of Things, Big Data and Artificial Intelligence. The Article states that "The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her." Automated processing is to be understood as "any form of automated processing of personal data consisting of the use of those data to evaluate certain personal aspects relating to an individual, in particular to analyse or predict aspects concerning that individual's performance at work, economic situation, health, personal preferences, interests, reliability, behaviour, location or movements". The GDPR (to apply as of 25 May 2018) also includes the principles of 'data protection by design and by default' with Article 25.2.

ePrivacy Directive and Proposal for a Regulation on privacy and electronic communication

As mentioned above, the **ePrivacy Directive 2002/58/EC**³²⁶ also contains provisions relevant for companies engaging in online tracking of consumers, for example via cookies³²⁷. The Directive prohibits any interference with the confidentiality of communications and the related traffic data by persons other than users, without the consent of the users concerned, except when legally authorised to do so (Article 5). The Directive requires data controllers to also obtain consent from the user prior to storing or accessing information (such as cookies) on the user's terminal equipment (Article 5.3.). In addition to the confidentiality of communications (Article 5), the Directive establishes that service providers shall inform the consumer/user on the types of traffic data that is being recorded (when consent has been given) while users/consumers' consent can only be given for the provision of value-added services addressed to them (Article 6).

In addition, the Commission made **a proposal for a Regulation on privacy and electronic communication**³²⁸ in January 2017. The proposal seeks to be consistent with the GDPR, to respond to the new technological realities and address some of the persisting issues described above. Article 5 ensures the confidentiality of the electronic communications data while Articles 6 and 7 list the limited permitted use of such data and the requirements regarding deletion of these data. According to Article 9, the user should be periodically reminded that he/she has a right to withdraw consent regarding such processing. In order to ensure alignment with the rest of the EU data protection framework, the Regulation is entrusted to the same data protection authorities responsible for the GDPR (Article 18).

Another key aspect is to simplify the rules on cookies. The making use of the processing and storage capabilities of terminal equipment and the collection of information from endusers' terminal equipment can only take place with the consent from the end-user, unless it is necessary for carrying out the transmission of an electronic communication over an electronic communications network; for providing an information society service requested by the end-user; or if it is necessary for web audience measurement, provided that such measurement is carried out by the provider of the information society service requested by the end-user. In addition, software placed on the market permitting electronic communications, including the retrieval and presentation of information on the internet,

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³²⁵ Idem⁹⁰

³²⁶ Directive 2002/58/EC of the European Parliament and of the Council of 12 July 2002 concerning the processing of personal data and the protection of privacy in the electronic communications sector ('Directive on privacy and electronic communications'). http://eurlex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:32002L0058:en:HTML

³²⁷ Further analysis on the ePrivacy Directive is included in Annex 2 (Legal review)

³²⁸ European Commission (2017), "Proposal for a Regulation on Privacy and Electronic Communications". Available at: https://ec.europa.eu/digital-single-market/en/news/proposal-regulation-privacy-and-electronic-communications

such as browsers, shall be required to offer the option to prevent other parties than the end-user from storing information on the terminal equipment of an end-user or processing information already stored on that equipment.

3.3.2. Online firms' transparency about personalisation practices and consumer concerns

Consumers' undermined trust in the market due to a lack of transparency in relation to the personal data collection and usage by online firms can hinder the benefits that e-commerce can bring to businesses and individuals. Hence it was investigated whether companies using personalisation techniques are transparent about data collection methods and the use of consumers' personal data (RQ4).

The study conducted by the UK Office of Fair Trading (OFT) in 2013 found that businesses should be more transparent about the information collected on their consumers and the way it is used for online personalising prices. As the study pointed out, "transparency, the ability to opt-out of the collection of information and understanding are crucial to developing and maintaining trust in online markets". The study found that personalisation practices may raise certain concerns related to transparency. Some of these examples are presented in the box below.

Box 1: Sources of concerns about personalisation practices according to OFT(2013) report

- Consumers cannot easily avoid personalisation if they wish to for example because the trader requires the consumer to sign in, where personalisation is conducted by a search engine or where personalisation is based on IP address, browser type, or the device used by the consumer;
- Consumers do not know it is occurring; or
- Consumers cannot easily see prices paid by other customers and prices are highly differentiated or many consumers receive some form of discount
- Consumers are subject to misleading statements or omissions when presented the price
- Consumers have expressed concerns in relation to their privacy due to two factors: 1) the fact that information on their online behaviour is collected by companies and 2) the subsequent use of that information to influence the prices they are offered when searching online

Two consumer surveys by the European Commission on cross-border obstacles to the Digital Single Market³³⁰ showed that the most common consumer concerns related to ecommerce are data protection, payment security and consumer rights: when it comes to domestic online shopping, 30% of consumers were concerned about the misuse of their personal data and 25% about the security of their payment card details.

These findings align with those of the consumer survey for the current study, which show that when it comes to online personalisation, consumers are most concerned about the usage of their personal data for other purposes/ by third parties, without their knowledge. For instance, when asked about this in relation to *online targeted advertising*, about half (49%) of respondents answered that they were concerned that their personal data could be used for other purposes and/or transmitted to others/3rd parties. Slightly more than half (52%-55%) of respondents in the consumer survey said that they would be more positive about online personalised practices if 1) it was explained what personal data was collected about them; 2) if they could see/change their personal data used for such practices; 3) it was explained for what purpose their personal data is collected; and 4) it was explained which 3rd parties access their personal data [see chapter 4 for more

³²⁹ OFT(2013).

³³⁰ GfK Belgium on behalf of the European Commission (2015): "Provision of two online consumer surveys as support and evidence base to a Commission study: Identifying the main cross-border obstacles to the Digital Single Market and where they matter most". Final report. Available at: http://ec.europa.eu/consumers/consumer_evidence/market _studies/obstacles_dsm/docs/21.09_dsm_final_report.pdf

information, in particular Section 4.4]. More than six in ten (62%) of respondents in the EU28 answered that they would be more positive about online personalisation (targeted advertising and personalised offers/ pricing) if there would be an easy option to "opt-out" of such practices.

The literature indicates that privacy policies may suffer from a lack of transparency. In 2015, *TIME.com* contacted the non-profit organisation "Center for Plain Language" to evaluate the privacy policies of seven technology companies³³¹. As pointed out by the Center for Plain Language, "a Privacy policy that consumers are unlikely to read or understand provides no protection whatsoever"³³². The Center assessed the companies' policies on several levels: the organisation and information design; the readability of the text (sentence length, structure, use of plain language) and the policies' compliance with the applicable privacy laws of their country/state. They also assessed whether the notice makes it easy for users to understand how the company is using and sharing their personal information and how the users can opt out. It should be noted that the study did not investigate what type of data companies collect from consumers or their subsequent use of these data. Instead, it focused on the clarity of companies in communicating their data collection and usage practices to users. According to the study, "the companies who did the best, avoided jargon and confusing sentence structure, clearly organized their information and used a lively tone"³³³.

It has been noted further in the literature that the links to the privacy statements on major UK websites do not always abide to these best practices. For instance, notices are often too lengthy and difficult to find (e.g. positioned at the bottom of the page in small font), which requires the consumers to actively look for the link to the privacy statement, rather than see it directly³³⁴. Furthermore, some important features of the website might cease to function properly (e.g. the shopping cart) if the cookies are disabled³³⁵. A Carnegie Mellon study (2008) found that the average length of privacy policies is 2,500 words and requires approximately 10 minutes to read, whilst the Internet user needs between 181 and 304 hours to read all privacy policies of the websites he/she visits yearly 336. In addition, privacy notices do not disclose "the full story" to consumers. For example, online firms inform consumers of their interaction with third parties, however they do not provide further information on who the third parties are or the ways they subsequently use the users' data. In fact, according to a study conducted by the Atlantic (2014), only 9 out of 50 websites mentioned in their privacy policies which third parties data is shared with³³⁷.

All of this might also lead to the consumer feeling like they do not have a real choice and so they are demotivated to inform themselves more. In fact, only a minority of consumers read the privacy policies, however this does not necessarily mean that they understand them³³⁸. According to the Consumerist (2012), only 20% of the consumers who have read the privacy policies claim to have a complete understanding of their content while for 37% the understanding was nearly none³³⁹. Even more, consumers seem to consider that there is a kind of 'trade-off' when it comes to privacy – meaning that in order to get better services, they have to 'pay' with their personal data, sometimes without truly knowing how

³³¹ Time, "These companies have the best (and worst) privacy policies". 6 August 2015. Available at: http://time.com/3986016/google-facebook-twitter-privacy-policies/

³³²Center for Plain Language (2015). Privacy Policy Analysis. Available at: http://centerforplainlanguage.org/wp-content/uploads/2015/09/TIME-privacy-policy-analysis-report.pdf

³³³ Time magazine referenced above³³¹

³³⁴ Mark Gazaleh, "Online trust and perceived utility for consumers of web privacy statements". Final project submitted in partial fulfilment of the requirements for the Master of Science degree in Eletronic Business.

³³⁵ Gazaleh(2008) referenced above³³⁴

³³⁶ Aleecia M.McDonald and Lorrie Faith Cranor, Carnegie Mellon, "The Cost of Reading Privacy Policies". Available at: http://lorrie.cranor.org/pubs/readingPolicyCost-authorDraft.pdf

The Atlantic, "Why privacy policies are so inscrutable". 5 September 2014. Available at: https://www.theatlantic.com/technology/archive/2014/09/why-privacy-policies-are-so-inscrutable/379615/
 Consumerist, "1-in-5 Internet users always read privacy policies, but that doesn't mean they understand what they're reading." 28 November 2012. Available at: https://consumerist.com/2012/11/28/1-in-5-internet-users-always-read-privacy-policies-but-that-doesnt-mean-they-understand-what-theyre-reading/

³³⁹ Consumerist (2012) referenced above ³³⁸.

the data will be used in the future. In a way, data privacy becomes either a necessary concession or a costly 'choice': "Privacy considerations leave the consumer with a dilemma. There is a positive trade-off between sharing personal data and getting better services. The efficiency of online services such as search engines can increase by giving these services more access to personal data. On the other hand, platforms may use this information for other purposes than to reply to a search query. They may use personal data to promote ad sales or simply sell the data to other platforms. Since the data subject is uninformed about these additional uses of his data and has no meaningful way to assess the implications, there is a risk involved. This creates a trade-off between ex-ante information costs and ex-post risks [...]. He may prefer to release less personal information and reduce these risks but consequently face higher search costs." 340

Furthermore, a 2007 Carnegie Mellon University study³⁴¹ found that when consumers were not presented with prominent privacy information, they were more likely to choose the vendor offering the lowest price. On the other hand, if presented with clear privacy information, consumers showed a preference for retailers who had stronger privacy policies.

The stakeholder survey which was also part of the current study also pointed to a current lack in transparency. In total, 11 out of 17 (or 65%) DPA and CPA survey respondents noted that usually business operators are not transparently informing the consumer regarding the collection of their personal data and the subsequent processing of it ('Usually No'). Only a very limited number of respondents (2 out of 17, across both respondent categories) indicated that business operators are usually transparent about their personal data collection and processing practices towards consumers. Experts, confirmed the finding from the literature review that even if these practices are explained via, for example, privacy statements, these are usually too lengthy, which means that consumers have little incentive to read them carefully. Business operators reported that according to them (5 out of 10), users are usually informed about personalisation or data collection practices through privacy or cookie notices. However, in line with the feedback from the experts and the findings from the literature review, the business operators acknowledged that consumers rarely read these notices.

Two of the companies offering personalisation solutions (out of 10 interviewed) in the stakeholder consultation noted that consumers have the right to access the datasets and approve, edit or request the deletion of the data collected on them in the databases of the companies. Thus, only the company itself and the consumers have access to the individuals' datasets. These stakeholders noted, however, that consumers rarely take advantage of this option. This might be explained by certain "usability" or" technological" barriers: even if consumers can approve, edit or request the deletion of the data collected on them, it may not be always clear how or where on the website to do this. One of the stakeholders in the survey also noted that some data analytics companies provide the personalisation solutions to other e-commerce companies. Therefore, consumers who would like to see the data collected on them cannot know who they have to request this data from.

In relation to the findings above about (the lack of) transparency about online personalisation, it is interesting to note that in the mystery shopping exercise for this study the shoppers could not find any information about why they were shown targeted adverts on 65% of the 141 (out of 717) website visits in which they believed to have noted these adverts³⁴². On slightly more than a quarter (28%) of the website visits in which shoppers

³⁴¹ Janice Tsai, Sege Egelman, Lorrie Cranor, Alessandro Acquisti. Carnegie Mellon University. "The Effect of Online Privacy Information on Purchasing Behaviour: an experimental study". June 2007. Available at: http://www.econinfosec.org/archive/weis2007/papers/57.pdf

Bertin Martens (2016), "An Economic Policy Perspective on Online Platforms". Institute for Prospective Technological Studies Digital Economy Working Paper 2016/05. JRC101501. Available at: https://ec.europa.eu/jrc/sites/jrcsh/files/JRC101501.pdf

³⁴²At the end of the mystery shopping exercise, shoppers were asked to indicate whether they believed to have observed personalised results on the website for which they recorded products and prices over several steps.

believed to have noted targeted adverts, shoppers noted a link/button to obtain more info on the advert and why it was shown. In less than one in ten (9%) of the website visits for which targeted adverts were reported, shoppers found information near/inside the advert explicitly stating that the advert was personalised.³⁴³.

Table 9: Information provided on targeted adverts, mystery shopping exercise

Was any information provided on why you were shown targeted adverts?	% of websites
No	65%
Yes, a link/button was shown to obtain more info on why you got the advert	28%
Yes, it was explicitly stated near/inside the advert that it was personalised	9%
Yes, using another method	3%

E2a. Was any information provided on why you were shown targeted adverts?

%, by website, Base: n=141website visits **Source: Mystery shopping exercise**

The next section explores online companies' compliance with the legislation provisions mentioned in Section 3.3.1.

3.3.3. Compliance of online business operators with the EU data protection/privacy and consumer protection regulatory framework

Are businesses which track consumers' online behaviour for personalised prices/offers compliant with the consumer laws and the existing EU regulatory framework, presented above? (RO6). This section presents the findings from the stakeholder consultation on this topic. It is important to note, however, that for some legal acts such as the ePrivacy Directive, depending on the country, there might be other competent authorities than the DPAs (e.g. telecom regulators) responsible for the enforcement of the Directive. Furthermore, the level of transposition of the ePrivacy Directive requirements may also vary per country. For example, a study conducted by Deloitte in 2016 showed that some provisions of the Directive have been implemented into national law in diverging ways and the Member States have encountered a number of challenges transposing it 344. In addition, the disparity of enforcement practices have resulted in under enforcement in some Member States. Given the considerable variations on the national level in the Directive's transposition, the effort to collect information from all responsible authorities in addition to the DPAs would have been particularly high. This study has thus limited the scope to DPAs in order to assess online firms' compliance with the EU Data Protection Directive and the GDPR as well as some aspects of the ePrivacy Directive. Hence, the stakeholder survey results do not necessarily provide a complete image of online firms' compliance with the EU data protection framework.

On 141 (20%) of all 717 website visits, shoppers reported to have observed targeted adverts. The shoppers somewhat less often indicated that they believed to have experienced personalised ranking of offers or personalised pricing (for 15% and 17% of all website visits, respectively, it was reported by the shopper that they believed to have observed these practices). It should be stressed that these are purely subjective observations that do not relate to the main, objective part of the mystery shopping.

³⁴³ When looking at personalised offers/pricing, we see that shoppers reported to be informed less often: on 82% of websites on which shoppers believed these practices occurred, no information was provided. Of course it should be taken into account that shoppers' subjective assessment about online personalisation was not necessarily correct.

³⁴⁴ Deloitte (2017), "Evaluation and review of Directive 2002/58 on privacy and the electronic communication sector". Available at: https://ec.europa.eu/digital-single-market/en/news/evaluation-and-review-directive-200258-privacy-and-electronic-communication-sector

Most experts consulted for this study noted that it is (legally) possible to both collect/acquire and transmit consumer data under payment in the EU, although to a much more limited extent that in the US, due to the different data protection regulatory framework. For example, it could be possible to do so if the consumers have been transparently informed about their personal data being processed and the use of their data or in cases, where the data has been anonymised and thus, the user is no longer identifiable. The practices of acquiring and transmitting consumer data could vary between the different Member States, according to 3 national experts. For example, it is more difficult to transmit data in countries with a strong data protection regulatory framework and enforcement such as Germany, Austria or the Nordic countries (as the processing of personal data is currently regulated by the Directive 95/46/EC which was implemented by Member States differently; the General Data Protection Regulation is to be applied directly in all Member States).

The EU legal framework³⁴⁵ requires the user's consent before information can be stored or accessed on the user's device. In relation to this, the majority of DPA respondents reported cases of failure of companies to provide adequate information to consumers (e.g. incomplete or misleading information clauses) and failure to obtain an informed consent from consumers in relation to data processing³⁴⁶. A number of DPA respondents argued that personalised pricing/offers could have a significant impact on consumers in cases where the offers are based on incomplete information/assumptions about the person's profile and are thus not accurate, or in cases where the offers are based on sensitive personal data (e.g. health, sexual orientation etc.). It is nevertheless important to note that half of the DPA respondents have rarely received complaints from citizens about personalised pricing/offers (6 out of 12), whereas 4 respondents noted that they never receive such complaints. Only 2 DPA respondents reported to receive either "frequently" or "occasionally" complaints on data protection issues related to personalised pricing.

The low number of complaints received by DPAs might partly be explained by the lack of awareness among consumers. Less than half (44%) of respondents in the consumer survey self-reported to be aware of online personalised pricing. For online targeted advertising and personalised ranking of offers awareness was higher (67% and 62%, respectively), but is should be stressed that self-reported awareness did not necessarily translate into an ability to recognise personalised practices when they occurred. In the behavioural experiment less than half of respondents were able to correctly identify online targeted adverts, personalised ranking of offers or personalised pricing, no matter the level of transparency in communication by the online platform and the personalisation scenario. When participants in the behavioural experiment did not receive transparent communication about online personalisation these figures were notably lower (for example, only 19% of participants correctly answered that they were personalised when results were sorted according to the browser they used and they were not informed about this). Furthermore, as observed above, DPAs are not always the competent authorities to enforce Article 5(3) of the ePrivacy Directive, thus the answers may be sometimes based on the perception of the respondents rather than reported cases of non-compliance.

The majority of CPA respondents indicated to have rarely received complaints regarding the non-compliance with consumer law and the EU regulatory framework³⁴⁷ of online firms. Out of 14 respondents, only one CPA respondent reported that his/her authority had received complaints about aggressive market practices by companies and the processing of personal data without the user's proper consent (violation of article 5(3) of the e-Privacy Directive on the confidentiality of the communications). Nonetheless, some respondents mentioned complaints in relation to online companies' lack of transparency on how personal data is processed, the transmission of personal data to third parties without the consumer's consent or knowledge and websites not allowing users to refuse cookies (See Annex 3 for full details on consumer complaints received by CPAs and DPAs). The mystery shopping

³⁴⁵ See article 5.3 of the ePrivacy Directive

³⁴⁶ Q14.1 from the survey to DPAs

³⁴⁷ Survey to CPAs, Q15 "In case there are business operators that are not compliant with consumer law and the EU regulatory framework in relation to personalised pricing/offers practices, how do they deviate from it?"

results also support the latter finding – refusing cookies was possible for only 22% of the mystery shopping visits.

The business operators' surveys provided further insights into companies' compliance with the GDPR and any difficulties they may be experiencing in the process. For example, 7 out of 10 respondents claimed to be either "almost ready" or "in the process of implementing the appropriate measures to ensure full compliance with the Regulation". Two respondents indicated that they are "considering ways forward" to ensure compliance. One respondent clarified that some companies, especially small ones, often do not have the resources to properly assess their compliance, as hiring external parties to perform gap assessments could be costly for them. Consequently, the respondent suggested that publicly available materials (e.g. guidance or manuals) on the requirements and the necessary actions for ensuring compliance with the GDPR could help companies to improve their understanding of the Regulation such as the manual launched by E-commerce Europe and the Irish E-commerce association "Retail excellence" in cooperation with the Irish Data Protection Commissioner³⁴⁸. Another respondent suggested that e-commerce or technology companies that are compliant with the GDPR can promote their privacy-by-design approach to gain a competitive advantage.

The literature review suggests that companies in the advertising sector target users based on sensitive personal data characteristics such as health or religion which is prohibited under the GDPR (Art 9 "Processing of special categories of data")³⁴⁹. However, the study cannot provide evidence on whether personalisation practices in general are compliant with the EU legal framework and the existing information in the literature is scarce when it comes to this issue, as the practices as such are not well understood by consumers.

3.4. Future evolution of personalisation practices in the online market as a result of technological advances

How are personalisation techniques likely to evolve in the context of the Internet of Things and Artificial Intelligence? Are they likely to further develop in the near future and become a typical pricing model of online sellers or is it likely to remain a pricing method to a small minority of online sellers? (RQ11)

It appears certain that personalisation will be an integral part of the future online market. The literature review showed that the use of consumers' data by the online sector will continue to grow with the evolution of technologies and devices which allow increasing amounts of information to be harvested and analysed. One trend to monitor is the exploration of "non-traditional data sources such as image, audio, and video files; the torrent of machine and sensor information generated by the Internet of Things" that only "few organizations have been able to explore" according to Deloitte Tech Trends (2017)³⁵⁰.

It has been noted that personalisation techniques would undergo a deep "paradigmatic" shift when programmatic advertisements (i.e. the use of software to purchase digital advertising) becomes the norm on more channels, in particular television. A technology called "addressable television" is already available, paving the way for personalised TV advertising, based on data on users' viewing customs. Other technological advances in this are being made, as evidenced by Google's investment in Invidi in May 2010 (Kafka 2010) and RTL's acquisition of the ad exchange SpotXchange in 2014.

Retail Excellence, Irish Ecommerce Association, "Retail Excellence and eCommerce Europe launch GDPR document for online retailers throughout Europe", Press release: https://www.retailexcellence.ie/wp-content/uploads/2017/10/Retail-Excellence-and-eCommerce-Europe-launch-GDPR-document-for-online-retailers-throughout-Europe-1.pdf

Garrascoca, et al⁴⁶
 Deloitte University Press, Tech Trends (2017), "Dark Analytics: Illuminating opportunities hidden within unstructured data", Available at: https://dupress.deloitte.com/dup-us-en/focus/tech-trends/2017/dark-data-analyzing-unstructured-data.html#endnote-17

³⁵¹ Gartner IT Glossary: https://www.gartner.com/it-glossary/addressable-tv-advertising/

Another emerging technology to watch is the use of Artificial Intelligence (AI) for detecting patterns in data collected on consumers' purchasing history, product and pricing preferences. This can be used for predictive recommendations, offers and prices. As with other technologies, this would be facilitated by the vast amount of data coming from the IoT increasing at an exponential rate. For instance, Gartner Inc. estimates that up to 20.8 billion connected devices and objects will be in use by 2020. Using IoT data, cognitive technologies such as machine learning "can provide a more personalized, contextual, and anticipatory service during the entire path to purchase", using algorithms to better match offers to consumers' preferences and to fundamentally change consumers' purchasing experience 354. Companies such as supermarket chain Kroger Co. are testing the use of IoT data in combination with cognitive analytics for interacting in-store with consumers, to tailor prices and products recommendations based on consumers' preferences 355.

The stakeholders interviewed for this study advocated that companies are already nowadays and will be increasingly using data on consumers' in-store physical location and movements (gathered by retailers and supermarket chains) in combination with their online behavioural data. The data collection and tracking is mainly performed through consumers' mobile apps and devices that are connected to the store's network. The data collected from consumers' presence in a store could be combined with consumer data and profile information, especially if they are logged in the dedicated retailer's mobile app, to personalise better prices or offer consumers loyalty cards. In addition, in-store purchases can also be tracked via the loyalty cards; and data on physical characteristics detected by digital displays: the cameras behind digital displays (digital signage) found in public spaces such as information screens in stores are capable of detecting the gender, approximate age and, in some instances, the mood of the person in front of it. Thus, the screens are able to personalise their offer on-screen or the data could be combined in a similar manner as the approach described above. Experts noted that this practice will become increasingly popular in the upcoming years.

Worth mentioning in relation to emerging technologies and transparency is a 2015 study on the impact of Big Data and smart devices on privacy by the Directorate-General for Internal Policies of the European Parliament³⁵⁶. This study, which encourages privacy-by-design, establishes that the EU approach to emerging technologies should be user-centric, "placing the individual more firmly at the heart of technological development, through transparency, user control and accountability". The report also recommends that personal data protection should be based on "transparency from data controllers; clearer information on the purpose and mechanism of data processing (...) to ensure the quality of consent to such processing and that discriminatory practices are not taking place; and guarantee a strong level of protection in the transmitting of data to third parties and third countries".

The literature indicates that there are emerging technologies which could reinforce transparency and trust in the data-driven market. To get a better understanding of ways of improving consumers' trust, a study conducted on behalf of DG CNECT by the Cambridge

³⁵² Andrei Neagu, Retargeting blog (2016), "How Artificial Intelligence is reshaping eCommerce Personalisation".
Available at: https://blog.retargeting.biz/how-artificial-intelligence-is-reshaping-ecommerce-personalisation/

³⁵³ Gartner Inc. (2015), « Gartner says 6.4. billion connected things will be in use in 2016, up to 30 percent from 2015", Press release http://www.gartner.com/newsroom/id/3165317

³⁵⁴ Deloitte University Press (2015), "The thinker and the shopper: Four ways cognitive technologies can add value to consumer products". Available at: https://dupress.deloitte.com/dup-us-en/focus/cognitive-technologies/artificial-intelligence-consumer-products.html

³⁵⁵ Kim Nash, WSJ (2017), "Kroger Tests Sensors, Analytics In Interactive Grocery Shelves", Article. Available at: http://blogs.wsj.com/cio/2017/01/20/kroger-tests-sensors-analytics-in-interactive-grocery-shelves/

³⁵⁶ Directorate General for Internal policies, Policy Department C: Citizens' Rights and Constitutional Affairs;

[&]quot;Big data and smart devices and their impact on privacy". Available at: http://www.europarl.europa.eu/regdata/etudes/stud/2015/536455/ipol_stu(2015)536455_en.pdf

University Business School ³⁵⁷ examined the concept of platforms such as "personal data stores" (PDS) that enable consumers to access, manage and transmit their personal data with businesses in a transparent, trusted and informed manner. The purpose of such data management stores is to increase consumer trust and engagement, while also serving as a transparent exchange platform. This way the consumers are empowered to follow the flow and use of their data, as well as the way their personal information is being collected. In case consumers give informed consent to third parties to access their data – which also allows third parties to access it – they can receive better-personalised offers, based on their preferences. A similar approach is the concept of "smart disclosures" – when public or private entities allow consumers to access the data collected on them in a user-friendly electronic format and enable consumers to make better informed choices³⁵⁸.

To conclude this section, it is worth noting that 8 out of 10 business operators that responded to the business survey supported that emerging technologies such as Artificial Intelligence in combination with data analytics/machine learning and the Internet of Things will have an important impact on personalisation practices in the upcoming years. More specifically, 3 of these 10 business operators were personalisation companies already making use of such technologies themselves, while 4 additional respondents were ecommerce websites that expressed the intention to use technologies such as IoT, data analytics or Virtual/Augmented reality in the next 5 years. Two respondents from the stakeholder survey replied that they are not planning to adopt these technologies due to the high costs involved, the little impact that they will have on their business model, or the lack of clarity with regards to data protection rules.

3.5. Summary of results – Online sellers: the data ecosystem, type of personal data collected, transparency in communication and compliance with relevant EU and national legislation

In the box below the key findings of this chapter are summarised.

Box 2 : Summary of findings – Online sellers: the data ecosystem, type of personal data collected, transparency in communication and compliance with relevant legislation

Type of personal data collected

- The data collection possibilities on the online market are virtually infinite. Personal data can be volunteered or surrendered by online users themselves (e.g. when creating accounts online), observed (e.g. when browsing history is tracked using cookies) or inferred (e.g. by combining and analysing data collected from different sources, such as data brokers). Online firms use a wide range of methods and technologies to collect this data.
- Online firms collect any type of personal data. For example, socio-demographic data (age, gender, etc.), behavioural data (history of website visits, clicks on ads, etc.), technical data (IP address, type of browser etc.). This may potentially include sensitive personal information on health, religion, and/or sexual orientation, etc.
- Companies do not necessarily seek to identify directly the individual by name as they are in particular interested in information on consumers' interests and behavioural characteristics, which allow them to segment and target different consumer groups collectively. This, however, does not exclude the possibility of individuals being identified (see below).
- Most companies claim to use "pseudonymisation" and "anonymisation" techniques to minimise the data protection risks for consumers, however these techniques do not necessarily prevent the re-identification of individuals. For example,

³⁵⁷ European Commission (2015), "Study on Personal Data Stores conducted at the Cambridge University Judge Business School. Available at https://ec.europa.eu/digital-single-market/en/news/study-personal-datastores-conducted-cambridge-university-judge-business-school

Tim O'Reilly (2012), "What is smart disclosure?". 1 April 2012. Available at: http://radar.oreilly.com/2012/04/what-is-smart-disclosure.html

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pseudonymisation is achieved by replacing the identifying characteristics, but allows for the indirect identification of the individuals. Furthermore, companies often claim to use anonymisation while in reality, they are applying pseudonymisation. As a result, the distinction between personal and non-personal data is less clear.

 Business operators can use online personalisation to target certain types of sociodemographic consumer groups differently, segmenting users based on their willingness to pay, or in some cases reported in literature, based on traits associated with vulnerable groups (e.g. health, race, sexual orientation etc.)

Technologies and means used for collecting personal data

- Online companies use various tracking methods/technologies to follow consumers across different platforms, websites and devices. The use of cookies is the most prevalent and traditional tracking method which can be easily prevented by users by deleting or disabling them in their browser. However, the consumer survey shows that less than a third (30%) of respondents always or very often delete cookies.
- Companies increasingly make use of more advanced tracking technologies, such as web beacons and digital fingerprinting, to circumvent cookies' constraints. These are far less easy for consumers to prevent without extensive IT knowledge or without compromising the surfing experience
- Pricing algorithms are increasingly used for price discrimination, as well as for dynamic pricing. Algorithms can result in "perfect price discrimination" which could theoretically benefit consumers, for example by offering lower prices to consumers with a lower willingness-to-pay. However, pricing algorithms may also lead to unfair discrimination (e.g. based on gender, race etc.). The impact that dynamic pricing set by algorithms has on consumers is unclear, as sellers do not necessarily sell their items at the lowest price on the contrary, the desk research found evidence that some traders sell up to 40% higher than the initial minimum price set for the product.
- Specialised data analytics companies and data brokers offer personalisation software or data analytics services to e-commerce companies for the optimisation of their marketing and pricing strategy. Online firms also give data brokers access to their customer databases in order to combine their customer data with data from the data brokers' own database.
- The most commonly used tools that can help consumers prevent tracking and personalisation, such as ad blockers, private browsing mode, deleting or blocking cookies and activating the 'do-not-track' (DNT) option in the browser, offer limited protection. For example, DNT requests are almost never taken into account by Online Behavioural Advertising (OBA). Consumers can use more advanced web tools to prevent tracking (VPNs, TOR browser, anti-tracking browser extensions), however awareness about these tools appears to be low. For example, in the consumer survey 60% indicated to never use or to not know about tools to hide their IP addresses.

The overall data ecosystem and companies transmitting consumer data used for personalisation purposes

- The data market is highly complex with many actors. The same company may potentially both collect and transmit data. The marketing data and advertising industry is among the largest sectors in this ecosystem, which encompasses marketing agencies, data brokers, online advertisers, and e-commerce companies.
- E-commerce websites may not directly collect consumer data and convert into profiles as such, but rather use other specialised companies' personalisation or analytics software or services instead to obtain more refined consumer profiles.
- Data can be collected/obtained or transmitted in anonymised, pseudonymised and non-anonymised form by companies in the advertising sector. Social networks, ecommerce and collaborative platforms as well as advertising companies collect large amounts of data on consumers, which they often combine with additional

data obtained through other means (e.g. data brokers, digital publishers, market research companies, business partners, affiliated companies) to profile and segment consumers. The created profiles are used during "online ad auctions" where advertisers calculate their bid based on the information they have on the targeted consumer(s).

- It appears that B2C online marketplaces do not frequently transmit personal customer data to their online sellers. Nonetheless, online platforms (like for example Facebook) may share information with third parties like advertisers, vendors and other partners.
- On the other hand, there exist specialised B2B data platforms on which various actors can have access to high quality (personal) data and can acquire/transmit this data. The proliferation of such platforms is likely to increase in the future.
- In general, the stakeholders (national experts) interviewed for this study reported to have limited knowledge on the transmission of consumer data because of a lack of transparency, making it difficult to quantify the prevalence of these practices.

Online firms' transparency about personalisation practices and consumer concerns

- The literature shows consumers are most concerned about the usage of their personal data for other purposes by third parties, without their knowledge (confirmed by the consumer survey for this study). And they fear that data transmissions to third parties could well be a common practice.
- The literature review, stakeholder consultation and mystery shopping exercise point to a lack of transparency of business operators when it comes to informing consumers about the collection of their personal data and the subsequent processing of this data. This may limit the benefits that e-commerce can bring to businesses and individuals.
- Online business operators and national experts in the stakeholder survey noted that consumers are in theory informed about personalisation and data collection via privacy statements, however due to their length and potentially complex language, these statements are rarely read. In addition, consumers rarely have a real choice when it comes to opting-out of/refusing being tracked online (e.g. a lot of websites do not allow that consumers refuse cookies or do not provide information about cookies, as showed by the mystery shopping).
- Some of the interviewed companies offering personalisation solutions mentioned that they give consumers the possibility to access the data collected on them and approve, edit or request the deletion of the data collected on them in the databases of the companies. However, consumers rarely take advantage of this option. This may be due to the fact that it is not very clear to them how to proceed or whom to request it from.

Compliance of online business operators with the EU data protection/privacy and consumer protection legal framework

- For feasibility reasons, the stakeholder survey was limited to Data Protection Authorities (DPAs) and Consumer Protection Authorities (CPAs) in order to determine whether online business operators comply with the EU data protection/privacy and consumer protection legal framework. As for some legal acts there might be other competent authorities (e.g. telecom regulators), the stakeholder survey did not provide conclusive evidence on the compliance of online business operators.
- The EU legal framework requires the user's consent before information can be stored or accessed on the user's device. In relation to this, the majority of DPA respondents reported cases of failure of companies to provide adequate information to consumers (e.g. incomplete information clauses) and failure to obtain an informed consent from consumers in relation to data processing.
- Most consulted CPA stakeholders reported to have received few complaints on online business operators' non-compliance in relation to personalisation practices.
 Some CPAs mentioned complaints in relation to online companies' lack of transparency on how personal data is processed, the transmission of personal data

- to third parties without the consumer's consent or knowledge, and websites not allowing users to refuse cookies.
- The fact that public authorities receive few complaints with respect to personalised practices cannot be interpreted that online firms comply with the relevant legislation. As the behavioural experiment showed, consumers' awareness of such practices when they occur is particularly low.
- The mystery shopping results supported the finding that refusing cookies is possible only on a limited number of websites.

Future evolution of the online market as a result of technological advances

- It appears certain that personalisation will be an integral part of the future online market.
- Personalisation techniques are also expected to shift to other more traditional channels, in particular TV where personalised advertising is likely to become the norm in the future.
- Emerging technologies such as Artificial Intelligence in combination with data analytics/machine learning and the Internet of Things will have an important impact on personalisation practices in the upcoming years, according to all respondents to the stakeholder consultation and business operators surveys.
- The concept of "personal data stores" enables data sharing between consumers and businesses in a transparent, trusted and informed manner, by allowing consumers to follow the use of their data, as well as the way information is being collected. Similarly, "smart disclosure" initiatives enable consumers to access their data held by various public and private entities and thus, inform themselves better on the way their information is being used.

4. Consumers' awareness and perception of personalised pricing/offers and problems reported

This chapter looks at consumers' awareness of online personalisation (both their self-declared awareness, as well as the objective findings from the behavioural experiment), how they perceive these practices, to what degree they see benefits and disadvantages, and at consumers' overall opinion of online personalisation. This chapter looks as well at consumers' reported bad experiences with online personalisation and at whether they have complained about these and to whom. In addition, findings are presented on consumers' online behaviour and usage of tools to prevent online personalisation.

4.1. Awareness of personalised practices

4.1.1. Consumer awareness: findings from the consumer survey

In order to measure to what extent online consumers *believe*³⁵⁹ *to be* aware of online personalised practices, respondents in the *consumer survey* were asked to what extent they knew about targeted adverts, personalised ranking of offers and personalised pricing and whether they understood them. The concepts of these three personalisation types were briefly explained to the respondents before the relevant question (see the consumer questionnaire, in Annex A1.5)³⁶⁰. Below the results of these questions are presented by personalisation type.

To begin with online *targeted advertising*: across the EU28, about two thirds (67%) of respondents reported to understand or have some understanding of how this personalisation practice works 361 . The self-reported awareness about targeted advertising varied between $79\%^{362}$ in Greece and $49\%^{363}$ in Spain.

³⁵⁹ Self-evidently these questions do not show to which extent consumers are actually aware, or would recognise online personalisation when it occurs; the results from the behavioural experiment presented below shed more light on this.

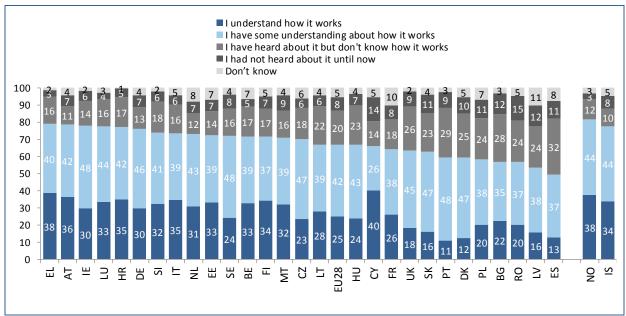
Briefly explaining the concepts of online targeted advertising, personalised ranking of offers and personalised pricing to respondents in the survey was deemed necessary as various terms are in use that cover similar practices (e.g. personalised pricing and price discrimination). This means that online consumers might not be aware of the term used even if they are aware of the practice, or might misinterpret the term for a different practice. The goal of the brief explanation of the term was to refrain as much as possible from providing information which could steer online consumers in a certain direction / to certain answers. Targeted advertising was for example explained as follows: "When you're looking online for goods and services, ecommerce websites can potentially access data on your online behaviour (searches, clicks, social media use, etc.), as well as personal information (e.g. age, gender etc.), tracked by themselves or by other websites you visited (e.g. via cookies). E-commerce websites can use this data to decide which adverts (banner ads, pop-ups, etc.) to show you. For example, an advert for a hotel that you could come across whilst browsing online your favourite news site, that clearly relates to your earlier online searches for hotels. This is known as online "targeted advertising"." For the similar explanation of online personalised (ranking of) offers and personalised pricing, see Annex A1.5.

This high level of self-declared awareness about targeted advertising is supported by previous studies in relation to online advertising. For example, in 2010 the UK Office of Fair Trading (OFT) commissioned a research study to investigate consumers' knowledge, experience and views of online targeted advertising. The study showed that most Internet users in the UK are aware of this practice and many believe that the use of such advertising is widespread. UK Office of Fair Trading (OFT) (2010), "Online targeting of advertising and prices", Market Study. Available at: http://webarchive.nationalarchives.gov.uk/20140402142426/http://www.oft.gov.uk/shared_oft/business_le aflets/659703/OFT1231.pdf

³⁶² The combined total is 79% in Greece due to rounding (and not 78% as the figure might suggest) as 38.4% answered "I understand how it works" and 40.37% answered "I have some understanding about how it works"

³⁶³ The combined total is 49% in Spain due to rounding (and not 50% as the figure might suggest), as 12.50% answered "I understand how it works" and 36.76% answered "I have some understanding about how it works".

Figure 24: Self-reported awareness of targeted advertising, split by country



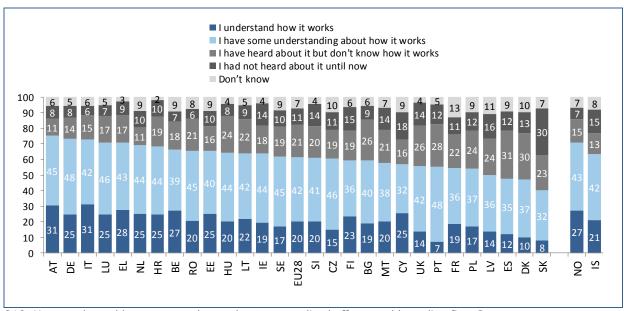
Q5. How much would you say you know about targeted advertising used by online firms?

%, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

In comparison to the self-reported awareness about targeted adverts, the self-reported awareness about *online personalised ranking of offers* (referred to as just "personalised offers" in the consumer questionnaire, for the sake of simplicity) was slightly lower. Across the EU28, slightly more than six in ten (62%) respondents reported to understand or have some understanding of how personalised ranking of offers used by online firms work. In Austria, respondents were the most likely to indicate that they understood or had some understanding of online personalised ranking of offers (75%), whilst respondents in Slovakia were the least likely to indicate that they understood or had some understanding of online personalised ranking of offers (40%).

Figure 25: Self-reported awareness of personalised ranking of offers, split by country



Q10. How much would you say you know about personalised offers used by online firms?

%, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

The self-reported awareness about *online personalised pricing* was on average quite lower than the self-reported awareness about online targeted adverts and personalised ranking of offers. Across the EU28, slightly more than four in ten (44%³⁶⁴ of) respondents reported to understand or have some understanding of how personalised pricing used by online firms works. In contrast, nearly 3 out of 10 (29% of) respondents mentioned that they hadn't heard of it up until now (versus only 8% and 11% for targeted advertising and personalised ranking of offers, respectively).

Like for the other two personalisation practices, some marked differences between countries can be observed. Whereas in Germany 57% of respondents reported to understand or have some understanding of personalised pricing, this figure was 29% in Denmark.

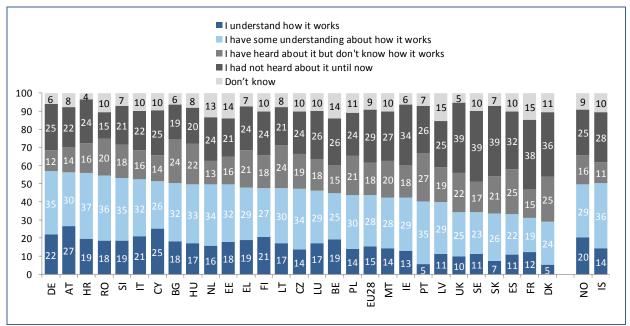


Figure 26: Self-reported awareness of personalised pricing, split by country

Q15. How much would you say you know about personalised pricing used by online firms? %, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

If we look at the self-declared awareness about personalisation methods among different socio-demographic groups, see table below, some limited differences can be observed. Male, younger respondents (16-34 years old), the self-employed, students, those with higher education, and those with no financial difficulties, were relatively likely to indicate that they understood how personalisation practices work. On the other hand, older (65+) respondents, those who are unemployed (including those looking for a job and those not looking for a job), those with lower education, and those respondents who find it very difficult to make ends meet, had a relatively low self-declared awareness about personalisation methods.

If we look at the awareness about personalisation methods for the group of respondents with a different online behaviour, we note more substantial differences. As might be expected, those who once a week or more often buy goods or services online, were significantly more likely to indicate that they understood how targeted advertising, personalised ranking of offers or personalised pricing work(s), compared to those who never or rarely buy products online.

³⁶⁴ 44% as 15.41% answered "I understand how it works", and 28.26% answered "I have some understanding about how it works".

Table 10: Self-reported awareness of personalised practices, split by socio-demographic

	Base (EU28)	Q5. How much would you say you know about targeted advertising used by online firms?	Q10. How much would you say you know about personalised offers used by online firms?	Q15. How much would you say you know about personalised pricing used by online firms?
		Net: Understan	d or have some	understanding
Average (EU28)	21,734	67%	62%	44%
EU Region				
EU15	11,832	68%	62%	43%
EU13	9,902	62%	58%	47%
Age				
16-34	8,196	70%	62%	45%
35-54	9,170	66%	62%	44%
55-64	2,992	64%	62%	43%
65+	1,376	58%	54%	38%
Gender				
Male	10,959	70%	66%	49%
Female	10,775	63%	57%	38%
Working status				
Employed	12,413	68%	64%	46%
Self-Employed	1,713	74%	69%	49%
Unemployed but looking for a job	1,416	60%	57%	33%
Unemployed & not looking for a job + other non-active*	3,961	58%	53%	37%
Pupil / Student / In education	2,231	72%	64%	47%
Living area				
Large town or city	8,145	68%	64%	46%
Small or medium sized town	8,474	66%	61%	42%
Rural area or village	5,115	65%	60%	43%
Education				
Low	2,250	53%	51%	34%
Medium	9,506	65%	61%	43%
High	9,978	73%		47%
Household financial situation				
Very easy	1,727	74%	70%	52%
Fairly easy	9,277	70%		47%
Fairly difficult	7,953	64%		41%
Very difficult	1,988	57%		36%
Frequency of purchasing products				
Once a week or more often	4,944	74%	71%	54%
Once a month or more often	8,500	70%		46%
Once every three months or more often	4,943	63%		37%
Once in the last 12 months or more often	2,317	51%		31%
Never	1,030	34%	30%	19%
* Sick/disabled, Housewife/homemake				
	,			

Source: Consumer survey

4.1.2. Consumer awareness: findings from the behavioural experiment

The behavioural experiment assessed participants' self-reported awareness of personalisation practices (i.e. whether they believed to have been personalised or not in the experiment), as well as whether participants accurately identified the type (if any) of personalisation practice they had experienced in the experiment. See Annex A1.8 for a detailed description of the methodology for the behavioural experiment.

The experiment found that participants tended to report greater awareness of personalisation practices if they received more transparent communication informing them that the product was recommended to them based on their previous searches. Furthermore, participants were more likely to correctly identify *personalised ranking of offers* if communication about online personalisation was transparent. However, greater transparency in communication by the online platform did not always help participants to correctly identify the other forms of personalisation.

It is important to note that when comparing the results from the consumer survey and the experiment, it can be observed that self-declared awareness does not necessarily imply that consumers recognise online personalised practices when confronted with them. *In the experiment*, the proportion of respondents that correctly identified targeted adverts or personalised ranking of offers/pricing was <50% for all personalisation practices and across the different levels of transparency in communication. This means that in the experiment the proportion of respondents that correctly identified targeted adverts or personalised ranking of offers/ personalised pricing is notably lower than the 67% of respondents in the *consumer survey* (see above) who indicated that they understood or had some understanding of targeted adverts, and 62% of respondents in the consumer survey who said that they understood or had some understanding of personalised ranking of offers³⁶⁵.

The following sections describe the behavioural experiment results regarding participants' self-reported awareness, and responses to objective questions identifying personalised practices.

Self-reported awareness of personalisation practices

This section examines the questions relating to the awareness of personalisation practices within the experiment by participants.

Proportion of respondents who believed there was personalisation in the experiment

Table 11 displays the proportion of participants in the experiment *reporting awareness* of personalised ranking of offers, personalised pricing and targeted advertising. For example, respondents were asked whether they believed that the order of the products had been personalised to them and if so, whether the personalisation was based on their previous search history or on their device and internet browser. The table presents the percentage of respondents indicating each option. *The table indicates respondents' beliefs about whether and how personalisation occurred, and does not indicate whether the responses were correct or not.* Respondents' answers to objective questions assessing their awareness are discussed in the section further below.

Panel A of Table 11 below shows responses to the post-experiment question relating to the ordering of products that respondents were shown. In the baseline case of no personalisation, 42.1% correctly believed that the order of the products shown to them had no particular pattern, approximately 40% answered that there had been some ordering

³⁶⁵ For personalised pricing, about which just 44% of respondents in the consumer survey reported to be aware, the differences with the experiment were less pronounced: the proportion of respondents in the experiment correctly answering whether they have experienced price personalisation varied between 33.7% in the low transparency treatment to 36% of in the high transparency treatments.

of the results (an incorrect response or 'false positive'), and 16.5% responded that they did not know.

In the low transparency treatment, where respondents were not given any indication that personalisation had occurred, a similar proportion (40.5%) of respondents across all scenarios believed that the order of the products had no particular pattern. However, in the high transparency treatments this falls to approximately 30% averaged across the high transparency treatment and the high transparency + action treatment, with a corresponding increase in the proportion of respondents identifying that personalisation had occurred. The difference in proportion of responses between the low transparency and high transparency treatments is statistically significant at 95%.

Overall, the introduction of the high transparency and high transparency plus action treatments lead to a statistically significant (at 95%) increase in the proportion of respondents believing that the products were based on the previous search information shown to them at the profile stage (39% and 35% in the high transparency and high transparency plus action vs 29% in the low transparency treatment).

There was no significant difference between high and low transparency treatments in the proportion of participants reporting awareness of other forms of personalisation, such as personalised prices or targeted advertising.

Table 11: Awareness of the ordering of products, by treatment

				High	
		Low	High	transparency +	Across all
	Baseline	transparency	transparency	action	treatments
	%	%	%	%	%
Panel A: Ordering of products					
The order of the products had no particular pattern	42.1	40.5	29.3	31.4	34.2
The order of some of the products was based on my previous searches shown to me	22.2	28.9	39.3	34.7	33.7
The order of some of the products was based upon the device and internet browser	19.2	18.9	21.4	24.0	21.3
Don't know	16.5	11.8	10.0	9.9	10.9
Total	100	100	100	100	100
N	346	2,086	2,070	2,078	6,580
Panel B: Prices of products					
The prices of the products shown had no particular pattern	40.3	37.5	38.3	38.3	38.1
The prices of some of the products seemed high compared to my previous searches shown to me at the beginning of the exercise	32.2	38.2	37.8	36.5	37.2
The prices of some of the products seemed low compared to my previous searches shown to me at the beginning of the exercise	15.0	15.1	15.1	16.2	15.4
Don't know	12.5	9.3	8.8	8.9	9.2
Total	100	100	100	100	100
N	346	2,086	2,070	2,078	6,580
Panel C: Awareness of advertis	ement				
Yes	46.8	43.1	44.1	41.9	43.2
No	53.2	56.9	55.9	58.1	56.8
Total	100	100	100	100	100
N	346	2,086	2,070	2,078	6,580
Panel D: Awareness of targeted	d advertisin	g			
The product was shown by chance or randomly	55.1	43.5	42.1	41.6	43.1
The type of product was based on the information on my previous searches shown to me at the beginning of the exercise	19.5	31.6	30.9	31.4	30.6
Don't know	25.4	24.9	27.0	27.0	26.3
Total	100	100	100	100	100
N	167	938	952	913	2,970

Note: Panel A: Question PP1. "Thinking about the [product] you just saw in the search results, in your opinion which of the following best describes **the order** in which they were shown to you?"

Panel B: Question PP2. "Thinking about the [product] you just saw, in your opinion which of the following best describes **the prices** of the products shown to you?"

Panel C: Question PP3. "Was there an advertisement on the screen just shown to you?"

Panel D: Question PP3a. "Thinking about the advertisement you just saw, in your opinion which of the following best describes the product that was advertised?"

Source: London Economics analysis of online experiment data

Proportion of respondents who believed personalisation had occurred, by scenario and treatment

A later post-experiment question explicitly told participants that some of them in the experiment had experienced personalisation, and asked them if they believed they had been one of those respondents. The table below shows the response to this question, which

shows that participants in the high transparency, and high transparency + action treatments had a greater awareness of personalisation in the experiment. Across all products, a significantly lower proportion of participants in the low transparency treatment reported that they believed personalisation had occurred, compared to participants in the higher transparency treatments. For example, among participants allocated to car rentals, 26% of participants reported that personalisation had occurred, compared to 35.7% of participants in the higher transparency treatments (on average). Results were more profound for holiday bookings (23% vs 37.9% on average).

Table 12: Did participants think they had experienced personalisation in the experiment, by product and treatment

Were you one of those participants?	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Car Rentals					
Yes	29.5	26.1	35.9	35.4	32.3
No	33.9	43.7	39.4	36.7	39.6
Don't know	36.6	30.2	24.7	27.9	28.1
N	100	595	591	593	1,879
TVs					
Yes	27.4	25.6	36.6	33.4	31.6
No	35.8	44.5	35.6	36.4	38.7
Don't know	36.8	29.9	27.8	30.3	29.7
N	123	744	740	743	2,350
Holiday bookings					
Yes	22.8	23.2	38.1	37.6	32.4
No	40.8	45.7	35.6	35.6	39.1
Don't know	36.4	31.2	26.3	26.8	28.5
N	123	747	739	742	2,351

Note: Question PP9. "For some participants, the [product] that they were shown had been personalised based on their [personalisation node]. Were you one of these participants?"

Source: London Economics analysis of online experiment data

The table below illustrates the proportion of participants reporting personalisation had occurred, by scenario and treatment. In the baseline scenario of no personalisation 26.5% of participants incorrectly believed they had experienced personalisation, and across personalisation scenarios with the low transparency treatment applied this figure is approximately 25%. In the high transparency treatments, however, this figure is substantially higher.

For example, in the personalised ranking of offers scenario where results were sorted based on the browser, 23.3% of participants in the low transparency treatment reported that their results had been personalised, compared to 33.5% of participants in the high transparency plus action treatment. The difference between low transparency and high transparency treatments was larger in the sub-scenario where results were sorted based on the participants' previous search history. Some 27.3% of participants in the low transparency treatment reported that results had been personalised, compared to an average of 45.1% of participants in the high transparency treatments. The difference between transparency treatments is statistically significant at 95%.

Similarly, in the price discrimination scenario, a significantly higher proportion of participants in the high transparency treatments reported that personalisation had occurred, compared to participants in the low transparency treatment.

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The responses of participants allocated to targeted advertising followed different patterns, depending on whether they experienced random sorting of search results, as opposed to when their search results had been sorted.

When search results are randomly sorted, the difference between low and high transparency treatments is not statistically significant (26.3% in the low transparency treatments, and 25.5% and 25.7% in the high transparency and high transparency+action treatments, respectively). This finding is consistent with the findings about the lack of attention paid to the advertisement (see Table 11).

Participants may also find it difficult to identify targeted advertising because it is a more subtle form of personalisation than price steering and price discrimination. However, participants were statistically significantly more likely to identify targeted advertising when combined with sorting of search results (a possibly more obvious form of personalisation) and greater transparency. More concretely, 21.9% of participants in the low transparency treatments identified personalisation when search results were sorted, compared to 36.1% of participants in the high transparency treatment, and 34.3% of participants in the high transparency+action treatment. The difference is statistically significant at 95%.

Table 13: Did participants think they had experienced personalisation in the experiment, by scenario and treatment

Were you one of those participants?	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
No personalisation					
Yes	26.5	-	-	-	-
No	36.9	-	-	-	-
Don't know	36.6	-	-	-	-
N	346				
Personalised ranking of	offers: res	ults sorted bas	sed on browse		
Yes	-	23.3	28.9	33.5	28.6
No	-	36.1	37.3	34.1	35.8
Don't know	-	40.6	33.8	32.4	35.6
N	-	345	342	345	1,032
Personalised ranking of	offers: res	ults sorted bas	sed on previou	s search results	
Yes	-	27.3	48.3	41.9	39.2
No	-	47.8	32.3	32.7	37.6
Don't know	-	24.9	19.4	25.4	23.2
N	-	345	347	347	1,039
Price discrimination: hig	h prices (b	ased on previ	ous search)		
Yes	-	23.3	42.6	40.3	35.2
No	-	40.5	30.9	34.6	35.4
Don't know	-	36.3	26.4	25.1	29.4
N	-	349	341	348	1,038
Price discrimination: lov	v prices (ba	ased on previo	us search)		
Yes	-	27.3	39.6	36.9	34.6
No	-	48.2	35.6	34.9	39.6
Don't know	-	24.5	24.8	28.2	25.8
N	-	351	345	344	1,040
Targeted advertising: ra	ndom sort	ing of search r	esults		
Yes	-	26.3	25.5	25.7	25.8
No	-	45.4	46.3	45.3	45.7
Don't know	-	28.3	28.1	29.0	28.5
N		346	353	349	1,048
Targeted advertising: so	rting of se				
Yes	-	21.9	36.1	34.3	30.8
No	-	49.9	37.5	35.3	40.9
Don't know	-	27.6	24.8	29.5	27.3
N		344	348	346	1,037

Note: Question PP9. "For some participants, the [product] that they were shown had been personalised based on their [personalisation node]. Were you one of these participants?"

Source: London Economics analysis of online experiment data

Participants from potentially vulnerable groups³⁶⁶ tend to report lower awareness of personalisation on average. For example, 38% of participants with low educational

³⁶⁶ Consumers who have difficulty making ends meet, with low educational attainment, who are not confident comparing offers, or who are economically inactive have been identified as vulnerable groups in previous research, including the European Commission study on Consumer Vulnerability across key markets in the European Union.

Consumer market study on online market segmentation through personalised pricing/offers in the European Union

attainment reported awareness of personalisation, compared to 46% of other participants. The difference is statistically significant at 95%. Similarly, a statistically significantly lower proportion of participants reported awareness of personalisation if they had difficulty making ends meet, or were inexperienced with online shopping. Awareness of personalisation practices was also different depending on the age group of the participant: only 36% of respondents 65 years and over reported awareness of personalisation across the three treatments, compared to e.g. 49% of respondents between the ages of 16 – 34.

However, in many cases, a significantly higher proportion of potentially vulnerable participants reported awareness of personalisation as transparency increased. For example, 39% of economically inactive participants reported awareness of personalisation in the low transparency treatment. But this proportion increased to 46% in the higher transparency treatments. Similarly, 34% of participants with low education reported awareness in the low transparency treatment, rising to approximately 44% in the higher transparency plus action treatment.

³⁶⁷ Analysis of participant responses by a full list of socio-demographic characteristics is provided in the Annex.

Table 14: Did participants think they had experienced personalisation in the experiment, by socio-demographic group, region and treatment

Were you one of those participants?	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Country group					
EU15	42	35	50	50	45
EU13	39	42	49	47	46
Age group					
16-34	49	40	56	53	49
35-54	34	36	50	49	45
55-64	51	28	42	46	39
65+	24	28	35	44	36
Gender					
Male	42	34	48	46	43
Female	41	38	52	53	48
Economic activity					
Active	43	35	52	51	46
Inactive	39	39	46	46	44
Educational attainment					
Medium/High	42	36	52	50	46
Low	38	34	36	44	38
Making ends meet					
Not difficult making ends meet	42	38	52	52	47
Difficult making ends meet	43	33	48	47	43
Experience with online to	ransaction	S			
Relatively experienced	44	36	51	50	46
Relatively inexperienced	31	31	40	40	37
N	346	2,086	2,070	2,078	6,580

Note: Question PP9. "For some participants, the [product] that they were shown had been personalised based on their [personalisation node]. Were you one of these participants?"

Participants are coded as finding it difficult to make ends meet if they indicate that they find it 'fairly difficult' or 'very difficult' to make ends meet.

Participants are coded as 'relatively inexperienced' with online transactions if they indicate that they use the internet to buy goods/services online once in the last 12 months, or less frequently.

Source: London Economics analysis of online experiment data

Participants in higher transparency treatments (where it was more prominently highlighted that products or prices are based on previous searches or a previous purchase) were also significantly more likely to report that they were aware of personalisation at the product selection stage rather than at the confirmation stage, compared to lower transparency treatments.³⁶⁸

³⁶⁸ Note that the participants in the baseline scenario did not experience personalisation, therefore their responses are 'false positives'.

Table 15 : At what stage did participants believe they had experienced personalisation, by treatment

Were you one of those participants?	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
I realised whilst on the results screen where I was shown the list of products	83.4	75.8	83.4	80.7	83.4
I realised whilst on the screen where I was asked to confirm my purchase	16.6	24.2	16.6	19.3	16.6
N	96	546	803	780	2,225

Note: Question PP10. "At what stage did you realise [that personalisation had occurred]?"

Source: London Economics analysis of online experiment data

Responses to objective questions about personalisation practices in the behavioural experiment, by treatment, scenario and socio-demographic group

In the behavioural experiment, participants were asked a series of questions exploring whether they had correctly identified whether and how the following were personalised to them: 1) offers (i.e. the ordering of products); 2) prices; and 3) advertising.

Proportion of respondents who correctly identified (if) offers were personalised

For all products, a significantly lower proportion of participants in the low transparency treatment *correctly identified* (i.e. when it had occurred) personalised ranking of offers than in the higher transparency treatments. For example, among participants allocated to car rentals, 28% in the low transparency treatment correctly identified personalised ranking of offers, compared to approximately 38% of participants in the higher transparency treatments (equally the same trend was observed for TVs). Among participants allocated to holiday rentals, 31% of participants in the low transparency treatment correctly identified personalised ranking of offers, compared to 43% of participants in the higher transparency treatments.

Table 16: Correct responses to objective questions testing awareness of personalised ordering of products, by product category

Scenario allocation	Base line	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Car rentals	46.1	28.2	40.1	36.1	35.4
N	100	595	591	593	1,879
TVs	38.5	27.6	39.8	37	35
N	123	744	740	743	2,350
Holiday rentals	42	31	44.3	42.3	39.4
N	123	747	739	742	2,351

Note: For each scenario (and in targeted advertising, the node of the scenario), the option that constituted the 'correct response' to each of the questions differed. The table shows the correct response to each scenario based on the individual correct response for each scenario.

Question PP1. "Thinking about the [product] you just saw in the search results, in your opinion which of the following best describes **the order** in which they were shown to you?"

Source: London Economics analysis of online experiment data

Table 17 displays the proportion of respondents who answered the question on the ordering of products correctly, by scenario and treatment. Across scenarios, respondents allocated to the high transparency and the high transparency + action treatments score more highly than those allocated to the low transparency treatment (41.4% and 38.6% against 28.9%), indicating that the additional messaging in the high transparency treatments raises awareness of personalisation. The difference in proportion of correct responses is statistically significant at 95%.

Participants also tend to perform differently depending on the scenario to which they were allocated as well as the transparency of communication. For example, only 18.8% of participants correctly answered in the low transparency treatment when results were sorted according to their browser, compared to 26.5% of participants in the low transparency treatment when results were sorted according to their previous search history. This difference is statistically significant at 95%. This is in line with the finding in Table 13, where relatively fewer participants reported that they had experienced personalisation in the node where products were sorted by browser, compared to by previous search history.

This suggests that consumers may find it more difficult to identify personalisation based on their browser rather than previous search history, which they may find easier to recall and link to personalisation. However, in both nodes, participants answered correctly significantly (at 95%) more often in the high transparency treatments. For example, when products were sorted based on previous search history, an average of approximately 42% of participants in the high transparency correctly identified personalised ranking of offers, compared to 26.5% of participants in the low transparency treatment.

Similarly, the proportion of respondents correctly identifying personalised ranking of offers is significantly higher (at 95%) in the high transparency treatments in the price discrimination scenario. For example, in the node where participants were shown higher prices based on their previous search, 30.2% of participants in the low transparency treatment correctly identified personalised ranking of offers. However, this proportion increased to 50% in the high transparency treatment.

However, transparency of communication makes less of a difference in the targeted advertising node where participants' results are randomly sorted (here the transparency related only to the display of the targeted ad only). Only between 40.3% and 42.2% of participants correctly answered that the products were not shown with any particular pattern, with no significantly difference between high and low transparency treatments.

But in the node where search results were sorted using personalised ranking of offers, transparency of communication significantly increased the proportion of participants answering correctly. 30.6% of participants in the low transparency treatment correctly answered, compared to an average of 40.5% of participants in the high transparency treatments.

However, the proportion correctly identifying personalisation remains low indicating how difficult it is for consumers to identify personalisation.

Table 17: Correct responses to objective questions testing awareness of personalised ordering of products, by scenario and treatment

Scenario allocation	Base line	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
No personalisation	42.1	-	-	-	42.1
Personalised ranking of offers: based on browser	-	18.8	29.5	31.3	26.5
Personalised ranking of offers: based on previous searches	-	26.5	47	37.1	36.9
Price discrimination: high prices	-	30.2	50	41.5	40.4
Price discrimination: low prices	-	27.4	40.4	39.5	35.7
Targeted advertising: random sorting of search results	-	40.3	40.7	42.2	41.1
Targeted advertising: sorting of search results (based on previous search)	-	30.6	40.9	40.1	37.2
Total	42.1	28.9	41.4	38.6	36.6
N	346	2,086	2,070	2,078	6,580

Question PP1. "Thinking about the [product] you just saw in the search results, in your opinion which of the following best describes **the order** in which they were shown to you?"

Source: London Economics analysis of online experiment data

Participants from potentially vulnerable groups tended to correctly answer questions testing awareness of personalised ranking offers less frequently than other participants. However, the difference is small and not statistically significant.

However, in many cases, a significantly higher proportion of potentially vulnerable participants reported awareness of personalisation as transparency increased. For example, 29.7% of economically inactive participants correctly identified personalised ranking of offers in the low transparency treatment. But this proportion increased to approximately 39% in the higher transparency treatments. Similarly, 27% of participants with difficulty making ends meet correctly identified personalised ranking of offers, compared to approximately 40% of participants in the higher transparency treatments. Moreover, 26% of participants with less experience of online transactions reported awareness in the low transparency treatment, rising to approximately 34% in the higher transparency treatments.

Table 18: Correct responses to objective questions testing awareness of personalised ordering of products, by socio-demographic group, region and treatment

Scenario allocation	Base line	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Country group					
EU15	45.8	29	41.7	39	37
EU13	23.2	28.7	40.1	36.7	34.5
Age group					
16-34	43	30	32	34	32
35-54	35	36	38	36	36
55-64	48	34	42	43	40
65+	47	44	34	39	39
Gender					
Male	38	35	37	36	36
Female	42	32	35	36	35
Economic activity					
Active	38.8	28.6	42	38.8	36.5
Inactive	51.4	29.7	40.2	38.2	36.8
Educational attainment					
Medium/High	44.7	29.3	41.7	39	37.1
Low	28.1	26.7	39.4	36	33.8
Making ends meet					
Not difficult making ends meet	43.3	30.5	41.8	39.2	37.5
Difficult making ends meet	36.8	27.2	41.5	38	35.7
Experience with online transaction	ıs				
Relatively experienced	40.5	29.3	41.6	39.9	37.1
Relatively inexperienced	50.7	25.9	40.4	27.7	33
N	346	2,086	2,070	2,078	6,580

Question PP1. "Thinking about the [product] you just saw in the search results, in your opinion which of the following best describes **the order** in which they were shown to you?"

Participants are coded as finding it difficult to make ends meet if they indicate that they find it 'fairly difficult' or 'very difficult' to make ends meet.

Participants are coded as 'relatively inexperienced' with online transactions if they indicate that they use the internet to buy goods/services online once in the last 12 months, or less frequently.

Source: London Economics analysis of online experiment data

Proportion of respondents who correctly identified (if) price personalisation was occurring

There is no substantial difference in the proportion of participants correctly identifying price personalisation between the low transparency and high transparency treatments, across products (Table 19) and scenarios (Table 20).

Table 19: Correct responses to objective questions testing awareness of price discrimination, by product and treatment

Scenario allocation	Base line	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Car rentals	43.5	32.8	34.7	38.9	35.9
N	100	595	591	593	1,879
TVs	34.6	32.9	40.1	33.6	35.5
N	123	744	740	743	2,350
Holiday rentals	43	35.4	33.6	36.8	35.7
N	123	747	739	742	2,351

Question PP2. "Thinking about the [product] you just saw, in your opinion which of the following best describes **the prices** of the products shown to you?"

Source: London Economics analysis of online experiment data

Table 20 shows the proportion of respondents who correctly responded to the question which asked them to best describe the pricing of the products they were shown. The correct answer to this question for those in the personalised ranking of offers and targeted advertising scenarios, was that the prices of the products shown had no particular pattern. It is only respondents in the price discrimination treatment that experienced either a level increase or decrease in prices shown compared to the prices provided at the initial profile stage.

Across all scenarios, there is very little difference in the proportion of respondents correctly answering whether they have experienced price personalisation, as transparency increases. Overall, 33.7% of participants in the low transparency treatment answered correctly, compared to approximately 36% of participants in the high transparency treatments.³⁶⁹

Relatively few participants in the price discrimination scenario correctly identified whether and how price personalisation had occurred. Specifically, less than 20% of participants correctly identified price personalisation in the sub-scenario where prices were lower based on the participants' previous search history. The proportion of participants correctly identifying that personalisation was occurring was lower in this sub-scenario compared to the personalised ranking of offers and targeted advertising scenarios, and these differences are statistically significant.

It appears that it is difficult for consumers to identify price discrimination on online platforms, which is in line with the empirical literature on price discrimination which has highlighted the difficulties researchers have found in detecting price discrimination (e.g. Hannak et al, 2014).

³⁶⁹ Across all products, there was no statistically significant difference between low and high transparency treatments in the proportion of participants correctly identifying personalised pricing.

³⁷⁰ This result may be due to participants' belief that if price personalisation has occurred, it is not beneficial to consumers. For example, almost 40% of participants in both price discrimination sub-scenarios incorrectly believed that prices were shown to them at random (not shown in Table 20). Approximately 37% of participants in both price discrimination sub-scenarios believed that prices were higher because of personalisation (not shown in Table 20). In the case of the 'higher prices' sub-scenario, this response was correct: prices were higher because of personalisation. However, in the case of the 'lower prices' sub-scenario, this belief was incorrect: in fact, prices were lower because of personalisation.

Table 20: Correct responses to objective questions testing awareness of price discrimination, by scenario and treatment

Scenario allocation	Base line	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Correct responses regarding the p	rices o	f products			
No personalisation	40.3	-	-	-	40.3
Personalised ranking of offers: based on browser	-	39.8	41.9	40.4	40.7
Personalised ranking of offers: based on previous searches	-	32.8	38	40.1	37
Price discrimination: high prices	-	36.6	42.8	36.8	38.7
Price discrimination: low prices	-	15.2	16.7	18.7	16.9
Targeted advertising: random sorting of search results	-	40.3	38	41.4	39.9
Targeted advertising: sorting of search results (based on previous search)	-	37.8	39.9	40.7	39.4
Total	40.3	33.7	36.2	36.4	35.7
N	346	2,086	2,070	2,078	6,580

Question PP2. "Thinking about the [product] you just saw, in your opinion which of the following best describes **the prices** of the products shown to you?"

Source: London Economics analysis of online experiment data

Participants from newer Member States tended to correctly answer questions testing awareness of price personalisation statistically significantly less often than participants from the older Member States. However, there was no statistically significant difference in the proportion of participants providing correct responses between low and high transparency treatments.

Participants from most of the potentially vulnerable groups tended to correctly answer questions testing awareness of price discrimination less frequently than other participants. However, the difference is small and not statistically significant. Similarly, there was no statistically significant difference in the proportion of correct responses between low and high transparency treatments.

Table 21: Correct responses to objective questions testing awareness of price discrimination, by socio-demographic group, region and treatment

Scenario allocation	Base line	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Country group					
EU15	41.9	34	37	37.8	36.6
EU13	32.1	32.3	32	28.8	31.1
Age group					
16-34	43	30	32	34	32
35-54	35	36	38	36	36
55-64	48	34	42	43	40
65+	47	44	34	39	39
Gender					
Male	38	35	37	36	36
Female	42	32	35	36	35
Economic activity					
Active	38.8	32.5	36.7	36.3	35.3
Inactive	44.6	36.6	35.1	36.5	36.4
Educational attainment					
Medium/High	42.6	33.7	36.1	36.5	35.8
Low	28.2	34.3	36.6	35.4	35
Making ends meet					
Not difficult making ends meet	42	33.8	35.8	38.4	36.3
Difficult making ends meet	40	34.4	37.3	33.6	35.3
Experience with online transaction	าร				
Relatively experienced	41.1	33.7	35.7	37.3	35.9
Relatively inexperienced	36.1	33.7	39.7	28.4	34.1
N	346	2,086	2,070	2,078	6,580

Question PP2. "Thinking about the [product] you just saw, in your opinion which of the following best describes **the prices** of the products shown to you?"

Participants are coded as finding it difficult to make ends meet if they indicate that they find it 'fairly difficult' or 'very difficult' to make ends meet.

Participants are coded as 'relatively inexperienced' with online transactions if they indicate that they use the internet to buy goods/services online once in the last 12 months, or less frequently.

Source: London Economics analysis of online experiment data

Proportion of respondents who correctly identified (if) targeted advertising was occurring

Panel A of Table 22 displays the responses to the question asking respondents whether there was an advertisement shown to them on the screens they had just been shown. Across all scenarios and treatments, over 50% of respondents failed to reply correctly when it comes to the presence or not of an advert shown, which fits in with the narrative of previous work which has shown the lack of effectiveness of banner adverts as consumers become more and more used to having adverts appearing online.³⁷¹

Similarly to the questions about the ordering and prices of the products shown, respondents who indicated that they had seen the advert in the experiment were asked which product had been shown, and whether it was shown by chance/randomly, or whether it was shown based on previous searches. The results are shown in Panel B of Table 22.

Approximately 40% of respondents who were allocated to the targeted advertising treatment (correctly) believed that the advertisement was targeted based on the previous search information they were given at the start of the experiment. However, there is little difference across treatments.

³⁷¹ Across all products, over 50% of participants failed to notice the banner advertisement. Note that in the personalised ranking of offers and the personalised pricing the ad was random.

Table 22: Correct responses to objective questions testing awareness of advertising, by scenario and treatment

Scenario allocation	Base line	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Panel A: Correct responses regard	ing the	presence of a	n advertiseme	nt	
No personalisation	46.8	-	-	-	46.8
Personalised ranking of offers: based on browser	-	46.2	45.1	44.3	45.2
Personalised ranking of offers: based on previous searches	-	46	37.8	41.7	41.8
Price discrimination: high prices	-	39.5	45.8	42.7	42.6
Price discrimination: low prices	-	45.2	48	42	45.1
Targeted advertising: random sorting of search results	-	44	46.5	41.5	44
Targeted advertising: price steering sorting of search results	-	37.9	41.6	38.9	39.5
Total	46.8	43.1	44.1	41.9	43.2
N	346	2,086	2,070	2,078	6,580
Panel B: Correct responses regard	ing the	product displa	ayed in the adv	vertisement	
No personalisation	38.3	-	-	-	38.3
Personalised ranking of offers: based on browser	-	32.8	37.2	33.7	34.6
Personalised ranking of offers: based on previous searches	-	31.8	34	28.1	31.2
Price discrimination: high prices	-	26.1	28	33.1	29.1
Price discrimination: low prices	-	39.4	31.9	24.8	32.2
Targeted advertising: random sorting of search results	-	43.8	35.5	45.4	41.3
Targeted advertising: price steering sorting of search results	-	41.6	37.4	36	38.3
Total	38.3	35.9	33.9	33.5	34.6
N	156	943	950	921	2,970

Panel A - Question PP3. "Was there an advertisement on the screen just shown to you?"

Panel B - Question PP3a. "Thinking about the advertisement you just saw, in your opinion which of the following best describes **the product that was advertisement?**"

Source: London Economics analysis of online experiment data

Participants from potentially vulnerable groups tended to correctly answer questions testing awareness of advertising less frequently than other participants. However, the difference is small and not statistically significant³⁷². Similarly, there was no statistically significant difference between the proportion of correct responses between low and high transparency treatments.

³⁷² The youngest group (16 – 34) is statistically significantly more likely (at 95%) to correctly answer objective questions testing awareness of advertising, compared to the oldest group (65+). However there is no difference on average between respondents aged 65+ and all other respondents.

Table 23: Correct responses to objective questions testing awareness of advertising, by socio-demographic group, region and treatment

Scenario allocation	Base line	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Panel A: Correct responses regard	ding the	presence of a	n advertiseme	nt	
Country group					
EU15	45.8	42.6	43.9	41.2	42.7
EU13	52	45.6	45.4	45.2	45.8
Age group					
16-34	51	48	48	45	47
35-54	44	43	44	41	43
55-64	47	37	38	38	38
65+	44	27	39	35	34
Gender					
Male	45	42	45	41	43
Female	48	44	43	43	44
Economic activity					
Active	47.9	44.3	44.4	44	44.4
Inactive	43.8	40.3	43.6	37.1	40.5
Educational attainment					
Medium/High	46.3	44.3	45.6	42.4	44.2
Low	49.6	35.7	34.7	38.3	37.1
Making ends meet					
Not difficult making ends meet	51.8	42.6	45	43.5	44.1
Difficult making ends meet	43.2	43.7	43.2	39.6	42.3
Experience with online transaction	ns				
Relatively experienced	47.2	43.6	43.7	42.8	43.5
Relatively inexperienced	44.8	38.9	47.4	34.5	40.7
N	346	2,086	2,070	2,078	6,580
Panel B: Correct responses regard					-,
Country group		,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	.,		
EU15	41.9	34	37	37.8	36.6
EU13	32.1	32.3	32	28.8	31.1
Age group	2211	32.3	-		0 2 . 1
16-34	53	37	40	36	38
35-54	29	37	31	34	34
55-64	27	29	32	29	30
65+	45	36	19	20	25
Gender	13	30	15	20	23
Male	43	34	32	31	33
Female	34	37	36	36	36
Economic activity	34	37	30	30	30
	20.0	32.5	36.7	36.3	35.3
Active	38.8		36.7	36.3	
Inactive Educational attainment	44.6	36.6	35.1	36.5	36.4
Educational attainment	42.6	22.7	26.1	26.5	25.0
Medium/High	42.6	33.7	36.1	36.5	35.8

Scenario allocation	Base line	Low transparency	High transparency	High transparency + action	Across all treatments
Low	28.2	34.3	36.6	35.4	35
Making ends meet					
Not difficult making ends meet	42	33.8	35.8	38.4	36.3
Difficult making ends meet	40	34.4	37.3	33.6	35.3
Experience with online transactions					
Relatively experienced	41.1	33.7	35.7	37.3	35.9
Relatively inexperienced	36.1	33.7	39.7	28.4	34.1
N	156	943	950	921	2,970

Panel A - Question PP3. "Was there an advertisement on the screen just shown to you?"

Panel B - Question PP3a. "Thinking about the advertisement you just saw, in your opinion which of the following best describes **the product that was advertised**?"

Participants are coded as finding it difficult to make ends meet if they indicate that they find it 'fairly difficult' or 'very difficult' to make ends meet. Participants are coded as 'relatively inexperienced' with online transactions if they indicate that they use the internet to buy goods/services online once in the last 12 months, or less frequently.

Source: London Economics analysis of online experiment data

4.1.3. Consumer awareness: findings from the stakeholder surveys

The figures from the consumer survey and behavioural experiment on the self-declared awareness about online personalisation appear to align with the findings from the stakeholder surveys. Close to half of the (combined) CPA and DPA respondents noted that in their opinion consumers are at least somewhat aware of the fact that online firms collect and process their personal data and data about their online behaviour: 7 out of the 19 stakeholders who answered this question believed that consumers are "somewhat aware", whilst only 1 stakeholder believed that consumers are "very aware". On the other hand, an equally large proportion (7 out of 19 respondents, 37%) of CPA and DPA respondents thought that consumers are "little aware". Another 2 out of 19 respondents from the stakeholder survey believed that consumers are not aware (11%) of the way in which online firms collect and process their personal data/data on their online behaviour.

4.2. Perceived benefits of personalised practices

4.2.1. Perceived benefits of personalised practices: Findings from the consumer survey

Do consumers see advantages of personalised practices? To provide an answer to this question, respondents in the consumer survey were asked about what they perceived as the main benefits of online targeted advertising, personalised ranking of offers and personalised pricing. Below the results of these questions are presented for each of the three personalisation types covered. Separate results are shown for respondents who indicated to have a full or some understanding of how the personalisation practice works, and for the average for all respondents.

When asked about the benefits of *online targeted adverts*, across the EU28, 42% of all respondents reported as the main benefit that it allows them to see the products that they might be interested in. Slightly less than a quarter (23%) mentioned as an advantage of online targeted adverts that they reduce the number of irrelevant adverts they see, while one in five (20%) saw as benefit that it helps to fund the internet and allows "free" content online. Roughly a quarter (24%) of respondents did not see any benefits of online targeted advertising.

The results are very similar for the respondents who indicated to understand or have some understanding of targeted adverts. As might be expected, this group did notably less often reply "don't know" when asked about what they perceived as the main benefits of targeted adverts and in general gave slightly higher percentages when it comes to the perceived benefits.

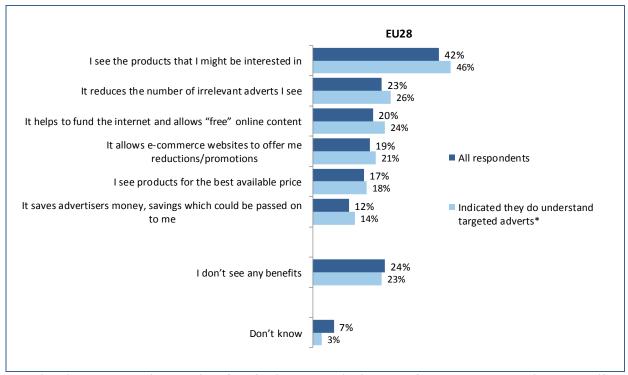


Figure 27: Perceived benefits of online targeted advertising

Source: Consumer survey

In the same manner, respondents were asked to indicate their three perceived main benefits of *online personalised ranking of offers*. Again, respondents were relatively inclined to answer that such practices allow them to see the products they are interested in. Across the EU28, 34% mentioned this as a benefit of online personalised ranking of offers. Roughly a quarter (23%) of respondents indicated as benefits of personalised ranking of offers that it either saves them time when searching online or that it allows them to more easily choose products that suit their needs. A quarter (25%) of respondents did not see any benefits of online personalised ranking of offers; a similar figure as for online targeted adverts.

When focussing on respondents who reported to understand personalised ranking of offers (in Q10), we see that this group selected "don't know" less often than the average respondent (4% vs 12%). The proportion in this group who do not perceive any benefits of personalised ranking of offers is similar to the average (24% and 25%, respectively), but as before higher percentages are given for the perceived benefits.

Q7. What do you see as the main benefits of online targeted advertising for internet users such as yourself? Select max. 3 answers.

^{% (}max. 3 answers), EU28, Base: All respondents (n=21,734); indicated to understand targeted adverts (n=14,653).

^{*}Indicated "I understand how it works" or "I have some understanding about how it works" in Q5.

EU28 34% I see the type of products that I might be interested in 40% 23% It saves me time when searching online 27% 23% I can more easily choose products that suit my needs 27% All respondents 18% It allows e-commerce websites to offer me reductions/promotions 22% Indicated they do understand 17% personalised offers* I get the best available price for products 19% 25% I don't see any benefits 24% 12% Don't know

Figure 28: Perceived benefits of online personalised ranking of offers

Q12. What do you see as the main benefits of online personalised offers for internet users such as yourself? Select max. 3 answers.

*Indicated "I understand how it works" or "I have some understanding about how it works" in Q10.

Source: Consumer survey

Respondents were asked as well about what they perceived as the three main benefits of online personalised pricing for internet users like themselves. About a third (32%) of respondents did not see any benefits of personalised pricing; a figure higher than the comparable figure for targeted adverts and personalised ranking of offers, practices for which about a quarter of respondents reported not to see any benefits. It should also be noted that more than a fifth (22%) of respondents answered with "don't know" when asked about what they saw as the three main benefits of personalised pricing. This appears to be in line with the relatively low overall awareness about personalised pricing.

Roughly a fifth (22%) of respondents indicated as a benefit of personalised pricing that it allows e-commerce websites to offer reductions/promotions. A similar proportion (21%) of respondents mentioned as a benefit of personalised pricing that it allows them to get the best available price for products.

When looking at respondents who indicated to understand personalised pricing (in Q15), we see that this group much less often answered "don't know" when asked about their perceived benefits of personalised pricing (7% vs 22%). However, like for the other two personalisation practices, this does not mean that this group of respondents is less negative about personalised pricing. About a third (31%) of respondents who indicated to understand personalised pricing (in Q15), did not see any benefits of personalised pricing, similar to the average for all respondents (32%). As before, these respondents gave higher percentages for all perceived benefits associated with this practice.

^{% (}max. 3 answers), EU28, Base: All respondents (n=21,734); indicated to understand personalised offers (n=13,259).

EU28 It allows e-commerce websites to offer me reductions/promotions 31% 21% I get the best available price for products 28% 15% It allows e-commerce websites to increase product choice (incl. products they would otherwise make a loss on) 21% All respondents It ensures I can get the product I want as the higher price 12% Indicated they do understand means that less people will buy it 18% personalised pricing* 32% I don't see any benefits 31% 22% Don't know

Figure 29: Perceived benefits of online personalised pricing

 $\overline{\text{Q}}$ 17. What do you see as the main benefits of online personalised pricing for internet users such as yourself? Select max. 3 answers.

Source: Consumer survey

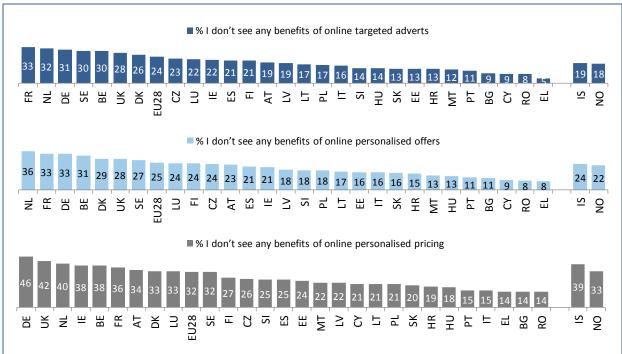
The country rankings for those who did not perceive any benefits of online targeted adverts, personalised ranking of offers³⁷³ and/or personalised pricing, show similarities across these types of personalised practices. A relatively high proportion of respondents did not perceive any benefits for all three types of personalised practices in countries like Belgium, France, Germany and the Netherlands, whereas in countries like Bulgaria, Cyprus, Greece and Romania, far less respondents reported not to see any benefits.

^{% (}max. 3 answers), EU28, Base: All respondents (n=21,734); indicated to understand personalised pricing (n=9,798).

^{*}Indicated "I understand how it works" or "I have some understanding about how it works" in Q15.

³⁷³ Referred to as online "personalised offers" in the questionnaire.

Figure 30 : Do not perceive any benefits of online targeted adverts, personalised ranking of offers and personalised pricing, split by country



Q7. What do you see as the main benefits of online targeted advertising for internet users such as yourself? Select max. 3 answers & Q12. What do you see as the main benefits of online personalised offers for internet users such as yourself? Select max. 3 answers & Q17. What do you see as the main benefits of online personalised pricing for internet users such as yourself? Select max. 3 answers.

% (max. 3 answers), by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513) [Same for all 3 questions]

Source: Consumer survey

As can also be made up from the previous graph, compared to respondents in the EU13, respondents in the EU15 were more likely *not* to perceive any benefits of the three personalisation practices. For instance, as can be seen in the next table, whilst in the EU15 more than a quarter (27%) of respondents did not see any benefits of personalised ranking of offers³⁷⁴, in the EU13 just one in six (16%) respondents did not perceive any benefits of this personalisation practice.

Older respondents and those unemployed and not looking for a job plus other non-active respondents were relatively much more *likely to not see any benefits* of the three personalisation practices. As might be expected, the same applied to respondents who never or seldom buy goods or services online. It should be added, however, that the mentioned socio demographic groups also frequently indicated "don't know" when asked about what they perceived as benefits of the three personalisation practices (see tables in Annex A4.2). It is interesting to note that those respondents who make ends meet very easily do not see benefits about personalised pricing distinctly more often than the other income groups (38% vs 30%). This was not the case with targeted adverts or personalised ranking of offers.

³⁷⁴ Referred to as online "personalised offers" in the questionnaire.

Table 24: Do not perceive any benefits of personalised practices, split by socio-

demographic group				
	Base (EU28)	Q7. What do you see as the main benefits of online targeted advertising for internet users such as yourself?	Q12. What do you see as the main benefits of online personalised offers for internet users such as yourself?	Q17. What do you see as the main benefits of online personalised pricing for internet users such as yourself?
			n't see any bene	
Average (EU28)	21,734	24%	25%	32%
EU Region EU15	11,832	26%	27%	34%
EU13	9,902	15%	16%	
	3,302	13 /0	10 /0	20 70
Age 16-34	8,196	18%	18%	27%
35-54	9,170	26%	27%	
55-64	2,992	31%	33%	
65+	1,376	33%	36%	
Gender	1,570	33 70	30 70	33 70
Male	10,959	23%	25%	31%
Female	10,775	25%	25%	
Working status	20,775	20 70	25 70	5275
Employed	12,413	23%	25%	31%
Self-Employed	1,713	28%	28%	
Unemployed but looking for a job	1,416	22%	19%	
Unemployed & not looking for a job + other non-active*	3,961	30%	31%	36%
Pupil / Student / In education	2,231	17%	18%	29%
Living area				
Large town or city	8,145	22%	23%	29%
Small or medium sized town	8,474	24%	25%	32%
Rural area or village	5,115	27%	29%	35%
Education				
Low	2,250	24%	24%	28%
Medium	9,506	25%	26%	30%
High	9,978	24%	25%	34%
Household financial situation				
Very easy	1,727	27%	27%	38%
Fairly easy	9,277	23%	24%	32%
Fairly difficult	7,953	24%	25%	30%
Very difficult	1,988	29%	28%	30%
Buy goods and services online				
Once a week or more often	4,944	17%	20%	
Once a month or more often Once every three months or more often	8,500 4,943	24%	24% 30%	
Once in the last 12 months or	4,543	20 70	30%	3370
more often	2,317	32%	34%	35%
Never	1,030	33%	31%	34%
* Sick/disabled, Housewife/homemak	er, Retired			

Source: Consumer survey

4.2.2. Perceived benefits of personalised practices: Findings from the stakeholder survey

In the stakeholder survey, CPAs were asked about what they thought were the main benefits of online personalisation according to consumers. These findings appear to align reasonably well with the findings from the consumer survey. The CPAs reported that consumers perceive as main benefits of online personalisation: 1) 'seeing products they might be interested in' (53%); 2) 'receiving special price discounts/promotions' (reported by 9 out of 17 respondents, or 53%); and 3) 'saving time when searching online' (reported

by 7 respondents). According to the CPAs, fewer consumers believe personalised pricing/offers help them to 'see products for the best available price' (4 respondents, 24%) and to 'receive relevant recommendations to similar products' (4 respondents, 24%).

4.3. Concerns with respect to personalised practices

4.3.1. Concerns with respect to personalised practices: findings from the consumer survey

Respondents in the consumer survey were asked to indicate their three main *concerns* with respect to online personalised practices. When asked about this in relation to *online targeted advertising*, about half (49%) of respondents answered that they were concerned that their personal data could be used for other purposes and/or shared with others/3rd parties. A similar proportion (46%) said that they were concerned about their online data being collected/ a profile being made about them.

Slightly more than a quarter (27%) of respondents said to be concerned about cookies being installed on their computer, whilst another quarter (25%) said to be concerned about not being able to refuse or "opt-out" of targeted advertising. It is worth stressing that just 7% of respondents indicated not to have any concerns about online targeted advertising.

Respondents who indicated to understand targeted advertising (in Q5), less often answered "don't know" when asked about their concerns with respect to this type of online advertising (3% vs 7%). For the rest the results for the respondents who indicated to understand or have some understanding of targeted adverts show the same trends as the results for all respondents, albeit with slightly more elevated levels of concerns.

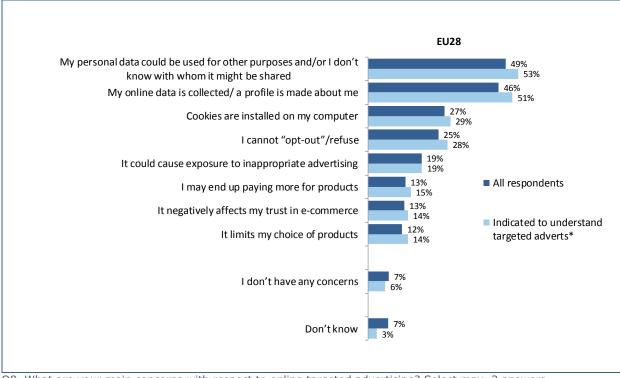


Figure 31: Concerns with respect to online targeted advertising

Source: Consumer survey

When looking at respondents' concerns vis-à-vis online personalised ranking of offers, a similar picture emerges as for online personalised adverts. Slightly less than half (46%) of all respondents answered that they were concerned about personalised ranking of offers because it could lead to their personal data being used for other purposes and/or shared

Q8. What are your main concerns with respect to online targeted advertising? Select max. 3 answers.

^{% (}max. 3 answers), EU28, Base: All respondents (n=21,734)

^{*}Indicated "I understand how it works" or "I have some understanding about how it works" in Q5.

with others/3rd parties. A similar proportion (42%) said that they were concerned about their online data being collected/ a profile being made about them.

As was also the case for targeted adverts, about a quarter (25%) of respondents listed concerns about cookies being installed on their computer among their three main concerns with respect to online personalised ranking of offers. A slightly lower proportion (22%) listed not being able to refuse or "opt-out" as one of their main concerns with respect to online personalised ranking of offers. About one in ten (9% of) respondents indicated not to have any concerns about online personalised ranking of offers – a similar figure as for targeted adverts (about the latter 7% did not have any concerns, see above).

When looking specifically at the group of respondents with at least some understanding of personalised ranking of offers (as indicated in Q10), it can be noted that this group answered "don't know" less often than the average respondent (4% vs 11%). The proportion of respondents in this group who did not have any concerns was the same as the average (9%). For the other answer items, slightly higher levels of concern are observed than for the average respondent. More than half (51%) of respondent who indicated to understand personalised ranking of offers said to be concerned about this personalisation practice because it could lead to their personal data being used for other purposes and/or shared with others/3rd parties (compared to 46% of all respondents who shared this concern). Almost half (47%) of respondents who indicated to understand personalised ranking of offers reported to be concerned about their online data being collected and/or a profile being made about them – the similar figure for all respondents was 42%.

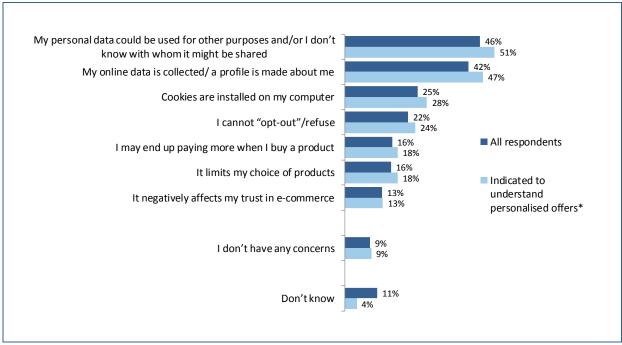


Figure 32: Concerns with respect to online personalised ranking of offers

Q13. What are your main concerns with respect to online personalised offers? Select max. 3 answers % (max. 3 answers), EU28, Base: All respondents (n=21,734)

*Indicated "I understand how it works" or "I have some understanding about how it works" in Q10.

Source: Consumer survey

As was the case with online targeted adverts and personalised ranking of offers, online personalised pricing primarily concerns respondents because they worry about the usage of their personal data. When asked about their main concerns in relation to personalised pricing, more than a third (36%) of respondents answered that they were concerned that their personal data could be used for other purposes and/or shared with others/3rd parties. A similar proportion (33%) said that they were concerned about their online data being collected/ a profile being made about them.

Somehow not unexpectedly, in relation to online personalised pricing, a relatively high proportion of respondents reported to be concerned about the effects on the price paid for products. More than a quarter (28%) listed "ending up paying more for a product" among their main concerns in relation to personalised pricing, compared to only 13%-16% who reported to be concerned about paying more for a product when asked about their concerns with respect to online targeted adverts and personalised ranking of offers. Just 7% of respondents indicated not to have any concerns about online personalised pricing – a similar figure as for online targeted adverts and personalised ranking of offers (practices about which 7% and 9%, respectively, of all respondents did not have any concerns). When comparing the average respondents with the respondents who indicated to have at least some understanding of personalised pricing (in Q15), it can be noted that the latter group of respondents was less inclined to answer "don't know" when asked about their concerns with respect to personalised pricing.

The overall pattern in responses was very similar for respondents who indicated to understand personalised pricing compared to all respondents, but with somewhat higher levels of concern, in line with what was observed for the other two online personalisation practices. More than four in ten (42%) of respondent who indicated to understand personalised pricing said to be concerned that this personalisation practice could lead to their personal data being used for other purposes and/or shared with others/3rd parties (compared to 36% of all respondents who shared this concern). Less than one in ten (8%) of respondents who indicated to have at least some understanding of personalised pricing reported not to have any concerns about this practice – the comparable figures for online targeted adverts and personalised ranking of offers were 6% and 9%, respectively.

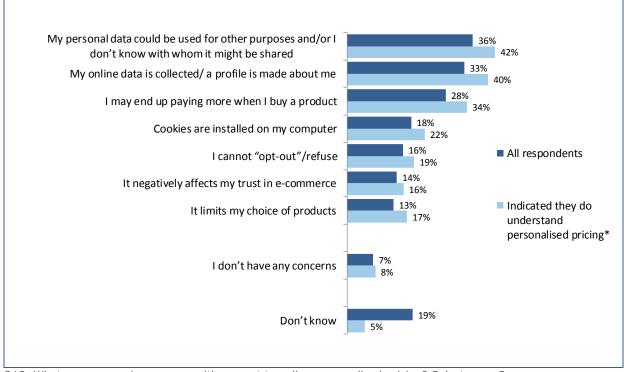


Figure 33: Concerns with respect to online personalised pricing

Q18. What are your main concerns with respect to online personalised pricing? Select max. 3 answers % (max. 3 answers), EU28, Base: All respondents (n=21,734)

*Indicated "I understand how it works" or "I have some understanding about how it works" in Q15.

Source: Consumer survey

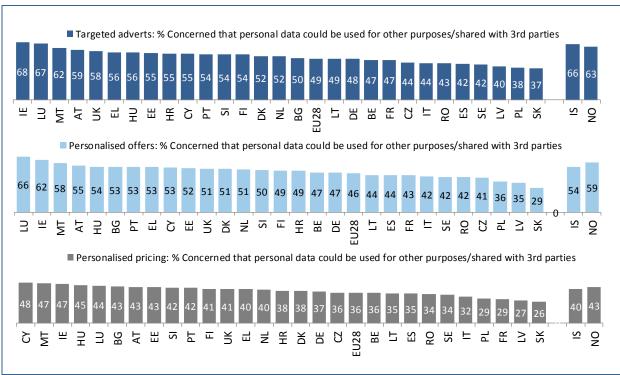
At country level, for targeted adverts, personalised ranking of offers³⁷⁵ and personalised pricing, concerns about personal data being used for other purposes/shared with 3rd parties, are particularly high among consumers in Ireland, Malta and Luxembourg. In

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³⁷⁵ Referred to as online "personalised offers" in the questionnaire.

Poland, Latvia and Slovakia, on the other hand, there appears to be much less concern among consumers about their data being used for other purposes/shared with 3rd parties, across personalised practices.

Figure 34 : Concerned that personal data could be used for other purposes/shared with 3rd parties, by personalisation practice, split by country



Q8. What are your main concerns with respect to online targeted adverts? Select max. 3 answers & Q13. What are your main concerns with respect to online personalised offers? Select max. 3 answers & Q18. What are your main concerns with respect to online personalised pricing? Select max. 3 answers.

% (max. 3 answers), by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513) [For all 3 questions]

Source: Consumer survey

At country level, noteworthy are also the large differences that can be observed for the concern "I cannot 'opt-out' / refuse" (see also overview in Figure 31, Figure 32 and Figure 33). For example, whilst only 7% of Hungarian respondents mentioned this among their top three concerns in relation to targeted advertising, this figure was 36% in Ireland, Austria and the UK. It can be noted that, across the three personalisation practices covered, concerns about the inability to "'opt-out' / refuse" was on average significantly higher in EU15 Member States compared to EU13 Member States.

■ Targeted adverts: % I cannot "opt-out"/refuse EU28 Personalised offers: % I cannot "opt-out"/refuse 28 EU28 ES Z = 2 ≥ BE EL 다 당 당 ■ Personalsied pricing: % I cannot "opt-out"/refuse EU28 ES 되 때 뜻 R C C 3 % &

Figure 35: Concerns about not being able to refuse / "opt-out", by personalisation practice, split by country

Q8. What are your main concerns with respect to online targeted adverts? Select max. 3 answers & Q13. What are your main concerns with respect to online personalised offers? Select max. 3 answers & Q18. What are your main concerns with respect to online personalised pricing? Select max. 3 answers.

% (max. 3 answers), by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513) [For all 3 questions]

Source: Consumer survey

Similarly, at country level, substantial variation can be observed in the proportion of respondents *not having any concerns*. For personalised pricing, for example, the proportion of respondents not being concerned at all varied between 2% in Luxembourg and Ireland and 16% in Croatia. The proportion of respondents without any concerns was on average significantly higher in EU13 countries compared to EU15 countries.

Figure 36: Proportion who do not have any concerns about online personalised practices, by personalisation practice, split by country

Q8. What are your main concerns with respect to online targeted adverts? Select max. 3 answers & Q13. What are your main concerns with respect to online personalised offers? Select max. 3 answers & Q18. What are your main concerns with respect to online personalised pricing? Select max. 3 answers.

% (max. 3 answers), by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513) [For all 3 questions]

Source: Consumer survey

At socio-demographic level, across the three personalisation practices, it is notable that particularly older (65+) respondents appear to be worried that their personal data could be used for other purposes and about exposure to inappropriate advertising. Younger (16-34) respondents and respondents currently in education/students (groups which show a substantial overlap), on the other hand, appear relatively worried about ending up paying more and not being able to opt out. For detailed figures, please refer to Annex A4.2.

4.3.2. Findings from the stakeholder survey with respect to concerns about personalised practices

As shown in the previous section, a high proportion of consumers reported to have concerns about the three main personalised practices covered by the study. On the other hand, it could also be noted that consumers also see advantages in online personalisation practices. In reference to this it is interesting to note that the findings from the stakeholder survey pointed to a moderate level of consumer concerns. The combined results for the DPA and CPA stakeholder surveys showed that only 3 out of 19 stakeholders reported that in their experience consumers are "extremely" or "very" concerned about the use of their personal data by online firms. The majority (13 out of 19) of stakeholders indicated to believe that consumers are either "somewhat concerned" (7 out of 19) or "little concerned" (6 out 19).

4.4. Reported experiences with personalised practices

4.4.1. Bad experiences with personalised practices and complaints

One of the aims of the consumer survey was to assess the nature, frequency and scale of problems consumers encounter with online personalised practices. The following figure presents the results of a question asking respondents whether they had actual bad experiences with targeted adverts, personalised ranking of offers, and/or personalised pricing.

It can be observed that the number of bad experiences reported is fairly similar across the three practices covered by this study. The top row of pie charts shows that the proportion of *all* respondents who reported bad experiences was 18% for online targeted adverts, 14% for online personalised ranking of offers (referred to as "personalised offers" in the questionnaire) and less so (12%) for online personalised pricing³⁷⁶. The latter result appears related to a high percentage of respondents not knowing if they encountered personalised pricing.

The second row of pie charts shows the results for the same questions, but now only for respondents who indicated (in Q5, Q10, Q15) to understand or have some understanding of the related personalisation practices. Compared to the average respondent, a higher proportion of respondents from the group with at least some understanding of the related personalised practices reported bad experiences, showing that there is a relation between the level of awareness and the number of bad experiences reported. This applied in particular to personalised pricing. Of the respondents who indicated to understand or have some understanding of personalised pricing, a fifth (20%) indicated to have had bad experiences with this practice (compared to 12% of all respondents who said to have had bad experiences with personalised pricing)³⁷⁷.

³⁷⁶ For online personalised offers and online personalised pricing this could be seen a remarkably high levels of reported bad experiences, considering that these practices appear hard to detect for the average consumer. The considerable number of reported bad experiences with personalised pricing also does not align with the low level of personalised pricing detected in the mystery shopping exercise for this study (see Chapter 5). It should be kept in mind, however, that these are self-reported bad experiences and that respondents have difficulties detecting online personalisation when it occurs (see Section 4.1.2 on the behavioural experiment). This means that a certain level of misinterpretation and overreporting cannot be excluded as potential explanations for the high level of reported bad experiences.

³⁷⁷ Of the respondents who indicated not to be aware about personalised pricing (in Q15), just 6% reported to have had bad experiences with this practice (in Q20a).

All respondents Targeted adverts Personalised offers Personalised pricing (EU28) (EU28) (EU28) 10% 12% 13% 18% 22% Yes No Don't know 66% 72% 72% Respondents who understand or have some understanding of the personalisation practice Personalised offers Personalised pricing Targeted adverts (EU28) (EU28) (EU28) 7% 9% 13% 20% Yes No ■ Don't know 72% 67% 74%

Figure 37: Bad experiences related to online targeted adverts, personalised offers and/or personalised pricing

Q20a. Have you had any bad experiences related to ...?

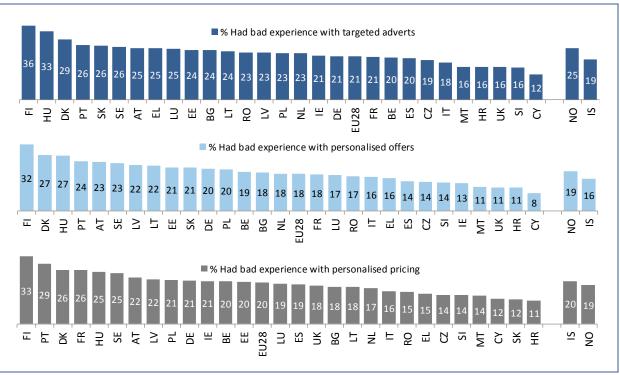
%, EU28, Base: All respondents (n=21,734); understand/ some understanding of targeted adverts (Q5, n=14,653), personalised offers (Q10, n=13,259), and personalised pricing (Q15, n=9,798).

Source: Consumer survey

The figure below shows the proportion of respondents who had a bad experience with the three personalisation practices at country level. The results shown are for those respondents who indicated (in Q5, Q10, Q15) to understand or have some understanding of the related personalisation practice.

This figure shows that in particular in Finland, Hungary and Denmark, across personalisation practices, a high proportion of respondents reported bad experiences. For example, 36% of the respondents in Finland, 33% of the respondents in Hungary and 29% of the respondents in Denmark reported bad experiences with targeted adverts. In Cyprus, Croatia and Malta, on the other hand, the proportion of respondents who reported bad experiences was relatively low across the three practices.

Figure 38 : Had bad experiences related to personalised practices <u>and</u> understand this practice, split by country



Q20a. Have you had any bad experiences related to ...?

%, by country, Base EU28: understand/ some understanding of targeted adverts (Q5, n=14,653), personalised offers (Q10, n=13,259), and personalised pricing (Q15, n=9,798).

Source: Consumer survey

The table below shows the *socio-demographic characteristics* of respondents who reported a bad experience with one of the three personalisation methods *and* who indicated to have some understanding of these practices. We can see that within this group of respondents, older respondents were least likely to report to have had bad experiences. This might partly be explained by the fact that older people also buy less frequently goods and services online (see Q1, Annex A4.2). Moreover, a higher proportion of those respondents with a higher education, as well as those who live in a large town/city, reported bad experiences.

Table 25: Had bad experiences related to personalised practices <u>and</u> understand this practice, split by socio-demographic group

	Had a bad experience with <u>targeted</u> <u>adverts</u>	Had a bad experience with personalised offers	Had a bad experience with personalised pricing
Average (EU28)	21%	18%	20%
EU Region			
EU15	20%	18%	20%
EU13	23%	19%	18%
Age			
16-34	23%	19%	22%
35-54	22%	18%	20%
55-64	17%	16%	16%
65+	12%	9%	10%
Gender			
Male	22%	19%	21%
Female	20%	16%	18%
Working status			
Employed	21%	19%	21%
Self-Employed	23%	18%	22%
Unemployed but looking for a job +	21%	15%	15%
other non-active*	19%	15%	15%
Pupil / Student / In education	20%	17%	20%
Living area			
Large town or city	24%	21%	21%
Small or medium sized town	20%	16%	19%
Rural area or village	18%	15%	18%
Education			
Low	17%	14%	14%
Medium	20%	17%	19%
High	22%	19%	22%
Household financial situation			
Very easy	22%	23%	25%
Fairly easy	20%	17%	19%
Fairly difficult	22%	18%	20%
Very difficult	20%	19%	19%
Frequency of purchasing products online			
Once a week or more often	24%	21%	24%
Once a month or more often	20%	17%	19%
Once every three months or more often	19%	15%	16%
Once in the last 12 months or more often	18%	15%	18%
Never * Sick/disabled, Housewife/homemaker, Reti	19% red	17%	15%

^{*} Sick/disabled, Housewife/homemaker, Retired

Q20a. Have you had any bad experiences related to...?

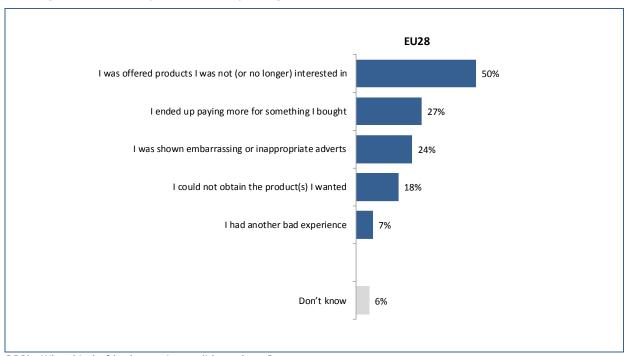
Source: Consumer survey

^{%,} by country, Base EU28: understand/ some understanding of targeted adverts (Q5, n=14,653), personalised offers (Q10, n=13,259), and personalised pricing (Q15, n=9,798).

The quarter (25%) of respondents who reported to have had a bad experience with either online targeted adverts and/or personalised ranking of offers and/or personalised pricing were asked about the type of bad experiences they had. By far the most recurrent answer across the EU28 was that they had been offered a product they were not or no longer interested in; half (50%) of respondents who reported a problem with any of the three covered personalised practices answered this³⁷⁸.

Slightly more than a quarter (27%) of respondents who reported a bad experience with online targeted adverts and/or personalised ranking of offers and/or personalised pricing indicated that they ended up paying more for something they bought, whilst slightly less than a quarter (24%) said that they were shown inappropriate adverts. Less frequently reported bad experiences were not being able to obtain the product that they wanted (18% reported this as bad experience).

Figure 39: Type of bad experiences with online targeted adverts and/or personalised ranking of offers and personalised pricing



Q20b. What kind of bad experience did you have?

% (multiple response), EU28, Base: Respondents who had a bad experience with targeted adverts, personalised offers and/or personalised pricing (n=5,568)

Source: Consumer survey

At country level, the proportion of respondents having had a bad experience with personalised practices who reported that they had been offered a product they were no longer interested in, varied between 65% in Lithuania and 21% in Cyprus. The proportion who ended up paying more ranged from 38% in Cyprus to 21% in the Netherlands, Slovenia and Greece.

Close to six in ten (57%) respondents in Hungary who had a bad experience with personalised practices, indicated that they encountered embarrassing or inappropriate adverts. In all other countries this figure was significantly lower, ranging from 40% in Greece to 10% in Cyprus.

³⁷⁸ Meaning that overall 12% of *all respondents* (when including those who did not report problems with the three covered personalised practices) reported to have been offered a product no longer interested in.

Figure 40: Type of bad experience, top 3, split by country

Q20b. What kind of bad experience did you have? – I was offered products I was not (or no longer) interested in %, by country, Base: Respondents who had a bad experience with targeted adverts, personalised offers and/or personalised pricing (EU28: n=5,568; NO: n=227; IS: n=110)

Source: Consumer survey

The socio-demographic characteristics of the respondents who indicated to have had a bad experience do not vary much. Noteworthy is that 55+ years old respondents noted frequently that they were offered products they were not or no longer interested in. Close to six in ten (57%) of the respondents in this age groups reported this, compared to on average half (50%) of respondents who indicated that they were offered products they were not or no longer interested in. For the full results by socio-demographic group for the question on the type of bad experiences encountered (Q20b), please refer to Annex A4.2.

4.5. Complaints about online personalised practices

4.5.1. Complaints about online personalised practices: findings from the consumer survey

EU regulation stipulates that, if individuals (including consumers) do not agree with how their personal data is collected and / or are not adequately informed about the purpose of data processing, they may reach out to any of the competent authorities to file a complaint³⁷⁹. But do consumers actually complain about online personalised practices?

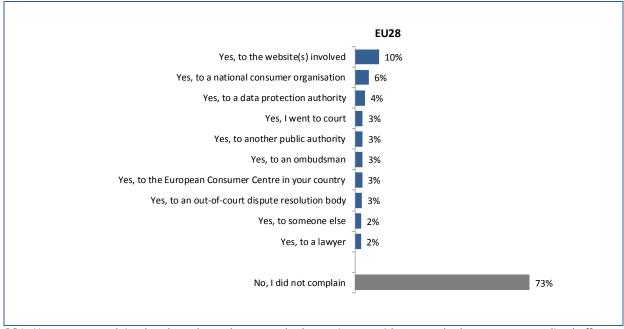
To answer this question, respondents in the consumer survey who indicated to have had bad experiences with personalised practices were asked whether they had complained about this and to whom. Of these respondents, close to three quarters (73%) said that they did not file a complaint. The remaining 27% who did complain, relatively often complained with the website(s) involved; one in ten (10%) of respondents with a bad experience with targeted adverts and/or personalised pricing and offers did the latter.

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³⁷⁹ The ePrivacy Directive 2002/58/EC applies when online personalisation is based upon technologies that store information, or upon gaining access to information already stored in the terminal equipment (e.g. when websites collect information, for instance by using profiling technologies such as tracking cookies, and transmit that information to third party data brokers, which is then used for online personalisation practices on other websites). Article 5 (3) of the ePrivacy Directive provides that such practices shall only be allowed upon the user's consent, after having been provided with clear and comprehensive information, in accordance with Directive 95/46/EC (to be replaced by the General Data Protection Regulation as of 25 May 2018).

Another 6% of respondents who had a bad experience with targeted adverts, personalised ranking of offers and/or personalised pricing complained to a national consumer organisation.

Figure 41: Have complained and to whom about bad experiences with online personalisation practices



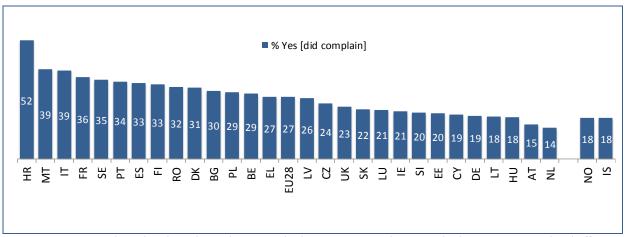
Q21. Have you complained and to whom about your bad experiences with targeted adverts or personalised offers and pricing? Select all that apply.

% (multiple response), EU28, Base: Respondents who had a bad experience with targeted adverts, personalised offers and/or personalised pricing (n=5,568)

Source: Consumer survey

The proportion of respondents who complained about a bad experience with targeted adverts and/or personalised ranking of offers and pricing, differs substantially across countries. In Croatia, more than half (52%) of those respondents who had a bad experience with one or more of the three personalised practices, did complain. At the other end of the country ranking, in Austria and the Netherlands, less than one in seven (15% and 14%, respectively) respondents with a bad experience did complain.

Figure 42: Have complained about bad experiences with targeted adverts and/or personalised ranking of offers and pricing, split by country



Q21. Have you complained and to whom about your bad experiences with targeted adverts or personalised offers and pricing? Select all that apply.

% (multiple response), by country, Base: Respondents who had a bad experience with targeted adverts, personalised offers and/or personalised pricing (EU28: n=5,568; NO: n=227; IS: n=110)

Source: Consumer survey

When looking at the results split out by socio-demographic group (see Annex A4.2 for Q21), we can observe little variation in results. In the 55-64 age group, 21% of respondents complained (lower than the average of 27%), but for the 65+ age group this figure (29%) was actually higher than the average. Respondents in rural areas were somewhat less likely to have complained compared to respondents from more urban areas (22% in rural areas vs. 29% in more urban areas).

4.5.2. Complaints about online personalised practices: findings from the stakeholder survey

The stakeholder survey confirmed the finding from the consumer survey that most consumers do not complain about their bad experiences with online personalised practices. Half of the DPA respondents in the stakeholder survey indicated that they rarely receive complaints from citizens about personalised pricing/offers practices (6 out of 12), whereas 4 DPA respondents noted that they never receive such complaints. Only 2 out of 12 DPA respondents reported to "frequently" or "occasionally" receive complaints related to personalised pricing/offers³⁸⁰.

The majority of the CPA respondents indicated that they rarely receive complaints from citizens about any types of personalised pricing/offers practices (12 out of 18, or around 67%). Moreover, 5 CPA respondents indicated to have never received any such complaints (28%). Only 1 (6%) CPA respondent declared that they occasionally received such complaints. No CPA respondent answered that they frequently or very frequently receive such complaints.

³⁸⁰ It should be noted that that DPAs are not necessarily the competent authorities to enforce Directive 2002/58/EC, as Member States are free to appoint the authority under the Directive (such as telecommunications regulators). This will change with the new ePrivacy Regulation which will ensure that the data protection supervisory authorities for monitoring the application of the GDPR will also be responsible for monitoring the application of the ePrivacy Regulation (Art 18). Currently, this depends on the national implementation of the ePrivacy Directive.

Nonetheless, for example 4 CPA respondents in particular indicated in the stakeholder survey to occasionally receive complaints about personal data being used for other purposes (see Annex A1.1.4).

4.6. Consumer's overall opinions on personalised practices: findings from the consumer survey

Respondents in the consumer survey were asked about their overall opinions about personalised practises to measure among other things whether they feel comfortable about their personal data being used by online firms to provide them with personalised ranking of offers. Below the related questions are described in detail for all respondents.³⁸¹

When asked about their overall opinion about *online targeted advertising*, about half (51%) of respondents across the EU28 reported to see both disadvantages *and* benefits³⁸². Slightly less than a third (29%) of respondents were more sceptical and saw primarily disadvantages. Just 9% of respondents across the EU reported to see primarily benefits when asked about their overall opinion about online targeted adverts.

At country level, substantial differences can be observed. Most notably, the proportion of those who thought that online targeted adverts primarily have disadvantages, varied between 39% in France and the Netherlands and 10% in Romania.

In only four countries (Bulgaria, Cyprus, Greece and Romania), there were more respondents who reported to see primarily benefits of online targeted adverts than there were respondents who reported to see primarily disadvantages of online targeted adverts. It should be added, however, that also in these countries the proportion of those who primarily saw benefits was low (ranging between 18% in Cyprus and 13% in Bulgaria).

³⁸² This is line with the findings from the behavioural experiment (Section 6.3), which shows that in general, participants tended to agree more with positive statements about personalisation (e.g. finding it useful to the overall process) compared to negative statements (e.g. finding it intrusive), whether they self-reported awareness of personalisation, or they were told about personalisation.

³⁸¹ The questions were analysed separately for respondents who indicated to have at least some understanding of the personalised practice in question. This did not show marked differences in results.

■I see primarily disadvantages ■I see primarily benefits ■I see both disadvantages and benefits ■Don't know 100 10 13 11 12 15 14 14 18 15 90 18 80 70 60 50 40 30 20 39 24 10 느쁘느 128 S 5 X Б SE \exists 正 š ΑT CZ ES 글 글 РТ ᇤ S ₹

Figure 43: Overall opinion about online targeted advertising, split by country

Q9. What is your overall opinion about online targeted advertising?

%, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

The figure below, displaying the overall opinion about *online personalised ranking of offers*, shows similarities to the figure on the overall opinion about online targeted advertising shown above; about half (49%) of respondents across the EU28 reported to see both disadvantages and benefits of personalised ranking of offers, whereas slightly less than a third (28%) perceived primarily disadvantages. Only 9% or respondents in the EU28 said to see primarily benefits when asked about their overall opinion about personalised ranking of offers, the same figure as for online targeted advertising.

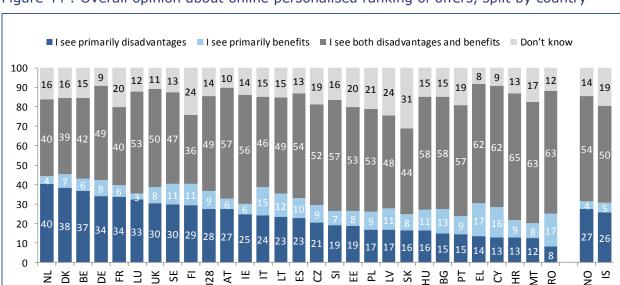


Figure 44: Overall opinion about online personalised ranking of offers, split by country

Q14. What is your overall opinion about online personalised offers? %, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

Just over a third (36%) of EU28 respondents said to see both disadvantages and advantages of online personalised pricing. This figure was notably lower than the

comparable figures for online targeted adverts and personalised ranking of offers (for which 51% and 49% reported to see both disadvantages and advantages, respectively). A third (33%) of respondents said to see primarily disadvantages of online personalised pricing, a similar figure compared to the 29% who said to see primarily disadvantages of online targeted adverts and the 28% who said to see primarily disadvantages of personalised ranking of offers. With 8%, the proportion of respondents who perceived primarily benefits of online personalised pricing was similarly low as the proportion of respondents who perceived primarily benefits of online targeted adverts and personalised ranking of offers. On the other hand, a relatively high proportion (24%) of respondents indicated "don't know" when asked about their overall opinion on online personalised pricing, as opposed to 11% and 14%, respectively, who indicated "don't know" for the other two types of personalised practices. This appears to align with the relatively low awareness about personalised pricing (see Section 4.1.1).

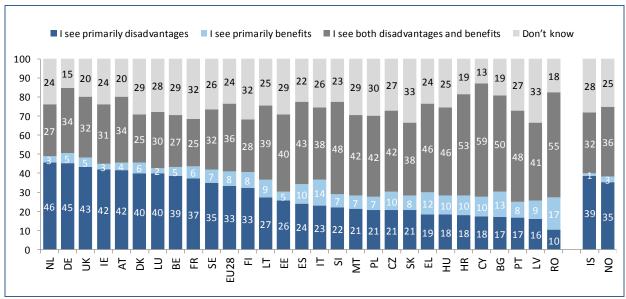


Figure 45: Overall opinion about online personalised pricing, split by country

Q19. What is your overall opinion about personalised pricing?

%, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

The table below shows the socio-demographic characteristics of the respondents who indicated to see primarily disadvantages of the three personalisation practices. Respondents from the EU15 were much more likely to see disadvantages as opposed to those who reside in the EU13. It can be noted that that the higher the age group the more negatively respondents feel about *all three personalised practices*. Interestingly, also the self-employed, those in a very easy financial situation and those with a higher education were more negative about *personalised pricing* (in particular), and less so about the other 2 practices, when compared to the average respondent.

Table 26: Overall opinion about online personalised practices, split by socio-demographic group

	Base (EU28)	Q9. What is your overall opinion about online targeted advertising?	Q14. What is your overall opinion about online personalised offers?	Q19. What is your overall opinion about personalised pricing?	
		See	primarily disadvant	iges	
EU28	21,734	29%	28%	33%	
EU Region					
EU15	11,832	32%	30%	37%	
EU13	9,902	18%	16%	19%	
Age					
16-34	8,196	27%	24%	32%	
35-54	9,170	30%	28%	33%	
55-64	2,992	32%	31%	36%	
65+	1,376	35%	33%	37%	
Gender					
Male	10,959	30%	28%	34%	
Female	10,775	29%	27%	33%	
Working status					
Employed	12,413	28%	27%	33%	
Self-Employed	1,713	32%	32%	40%	
Unemployed but looking for a job	1,416	28%	23%	27%	
Unemployed & not looking for a job + other non-active*	3,961	32%	31%	34%	
Pupil / Student / In education	2,231	28%	25%	35%	
Living area					
Large town or city	8,145	29%	27%	33%	
Small or medium sized town	8,474	29%	27%	32%	
Rural area or village	5,115	31%	28%	35%	
Education					
Low	2,250	25%	23%	24%	
Medium	9,506	29%	27%	32%	
High	9,978	31%	30%	39%	
Household financial situation					
Very easy	1,727	33%	32%	42%	
Fairly easy	9,277	29%	27%	36%	
Fairly difficult	7,953	29%	27%	30%	
Very difficult	1,988	32%	28%	30%	
Buy goods and services online					
Once a week or more often	4,944	26%	24%	32%	
Once a month or more often	8,500	29%	28%	36%	
Once every three months or more often	4,943	32%	30%	33%	
Once in the last 12 months or more often	2,317	34%	32%	32%	
Never	1,030	31%	27%	25%	
* Sick/disabled, Housewife/homemaker,					

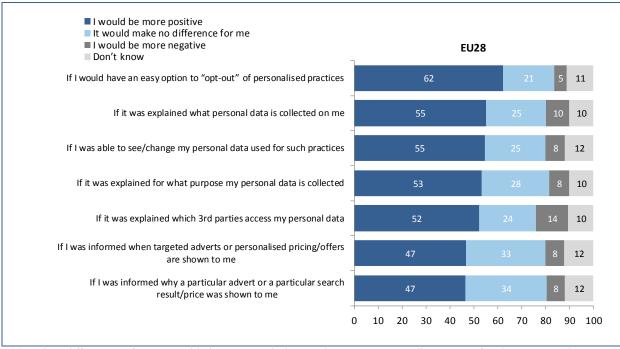
Source: Consumer survey

4.6.1. What would change respondents' overall opinion of online personalisation?

When asked what difference, if any, a number of listed options would make to their overall opinion about online personalisation (online targeted advertising, personalised ranking of offers and personalised pricing), slightly more than six in ten (62%) respondents in the consumer survey answered that they would be more positive if there would be an easy option to "opt-out" of such practices. Slightly more than half (52%-55%) of respondents said that they would be more positive if 1) it was explained what personal data was collected about them; 2) if they could see/change their personal data used for such practices; 3) it was explained for what purpose their personal data is collected; and 4) it was explained which 3rd parties access their personal data. Slightly less than half (47%) of respondents said that they would be more positive if they were informed when targeted

adverts or personalised pricing/offers are shown to them and if they were informed why a particular advert or a particular search result/price was shown to them.

Figure 46: What would change respondents' overall opinion of online personalisation (targeted advertising, personalised ranking of offers and personalised pricing)?



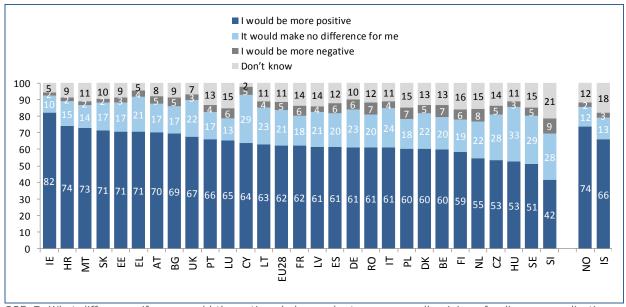
Q25. What difference, if any, would the options below make to your overall opinion of online personalisation (targeted advertising and personalised offers/ pricing)?

%, EU28, Base: All respondents (n=21,734)

Source: Consumer survey

At country level, the proportion of respondents who would be more positive about online personalised practices (online targeted advertising, personalised ranking of offers and personalised pricing) when they could have an easy option to "opt-out", varied between 82% in Ireland and 42% in Slovenia.

Figure 47: Easy option to "opt-out" of personalised practices as a reason to change opinion, split by country



Q25 $_$ 7. What difference, if any, would the options below make to your overall opinion of online personalisation (targeted advertising and personalised offers/ pricing)? – If I would have an easy option to "opt-out" of personalised practices

%, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

The proportion of respondents who would be more positive about online personalised practices (online targeted advertising, personalised ranking of offers and personalised pricing) when it would be explained what personal data is collected, ranged from 76% in Croatia to 44% in the Netherlands. In line with the previous figure on the option to "optout", respondents in Ireland, Malta, Greece and Slovakia were likely to indicate that their opinion would change in a positive way when they would be provided with information on the personal data collected.

■ I would be more positive It would make no difference for me ■ I would be more negative 10 14 11 12 10 13 11 EU28 UK FR AT FR DK CZ CZ SI SE s 5

Figure 48: Explanation of personal data collected as a reason to change opinion, split by country

Q25_4. What difference, if any, would the options below make to your overall opinion of online personalisation (targeted advertising and personalised offers/ pricing)? - If it was explained what personal data is collected on me

%, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

4.7. Feelings regarding personalised practices: findings from the behavioural experiment

This section covers the feelings that participants in the *behavioural experiment* reported after realising, or being told that personalisation practices were being applied to the search results they were shown.³⁸³

Experiment participants who reported that they became aware that personalisation was occurring, also reported at the end of the experiment that they found the personalisation useful to the overall purchasing process and that they liked it as their needs were catered for. On average these responses received a score of 3.4 out of 5, compared to an average score of 2.6 for 'I found it intrusive' and 2.3 for 'I was upset'. These differences are statistically significant at 95%.

Participants who did not realise that personalisation was happening during the experiment, but were informed at the end of the experiment, also tended to have more positive than

³⁸³ As a reminder, participants were randomly allocated to one of four scenarios: a 'baseline' scenario of no personalisation, or one of three personalisation scenarios, personalised ranking of offers, price discrimination and targeted advertising. Participants in the personalisation scenarios were also randomly allocated to one of three 'treatments' varying the communication of personalisation: low transparency where personalisation was not salient to participants, a high transparency treatment where personalisation was made salient, and a high transparency + action treatment where personalisation was salient and it was also easier for participants to clear cookies (i.e. a one-click process compared to three clicks).

negative feelings towards the personalisation. However, these participants were less positive and more negative than participants who had realised personalisation was occurring during the experiment. On average respondents gave a ranking of just over 3 out of 5 for 'I found it useful to the overall process' and 'I liked it as it catered to my needs'; and 2.9 for 'I felt it was intrusive' and 2.3 for 'I was upset'.

These observations from the experiment support the findings of the consumer survey that consumers see both positive and negative aspects to personalisation. For example, just over half of respondents in the consumer survey (51% across the EU28) reporting that they see both disadvantages and advantages when it comes to targeted advertising.

The main reasons participants had negative feelings about personalisation were around feelings that browsing data should be kept private with approximately 55% of respondents who reported they had negative feelings about personalisation stating this was a key reason. Other reasons were not liking websites building an online profile about their behaviour and habits, not knowing with whom their personal data might be shared (between 40% and 50%), and fear that companies will use personal data for purposes other than ones intended.

The reasoning behind participants' positive feelings towards personalisation related to time savings in searching online (between 57% and 63% depending on the personalisation scenario the respondent experienced), personalisation showing them more relevant products and allowing easier choice of products that suit their needs (approximately 50% across personalisation scenarios).

4.7.1. Participants' feelings about personalisation after self-reporting awareness of personalisation

Participants' feelings about personalisation

Participants who reported that they realised during the experiment that personalisation was occurring were asked to state using a 5 point scale how they felt about a range of statements, with 1 indicating totally disagree, and 5 totally agree. Responses to these questions are shown in Figure 49. This presents the average score for each statement by personalisation scenario. The averages are presented on a scale of 0 to 4 rather than 1 to 5 make the figure easier to read. Note a number of participants in the no personalisation treatment believed that they were experiencing personalisation when in fact they were not.

The statements with the most agreement were 'I found it useful to the overall purchase process' and 'I liked it as my needs were catered for', with scores of approximately 3.4. These scores were significantly higher than for the statements 'I found it intrusive' and 'I was upset' (2.6 and 2.3 respectively), indicating a positive response to personalisation by those respondents who became aware of the practices themselves during the experiment.

4.0 3.5 3.0 2.5 2.0 1.5 1.0 0.5 0.0 I found it intrusive I found it useful to the I liked it as my needs I did not have strong I was up set overall purchase were catered for opinions on it process ■ Personalised ranking of offers
■ Price discrimination
■ Targeted advertising
■ No personalisation

Figure 49: Feelings after realising personalisation had occurred, by scenario

Note: Question PP12a: "How did you feel after you realised you were seeing personalised results? Please select a number on the scale between 1 totally disagree and 5 totally agree for each statement." N=2,225. **Source: London Economics analysis of online experiment data**

Participants who recognised that personalisation was occurring in the experiment also tended to agree with positive statements regarding personalisation (e.g. finding it useful or liking it as their needs were catered for), rather than negative statements e.g. finding it intrusive or being upset, across all personalisation treatments.

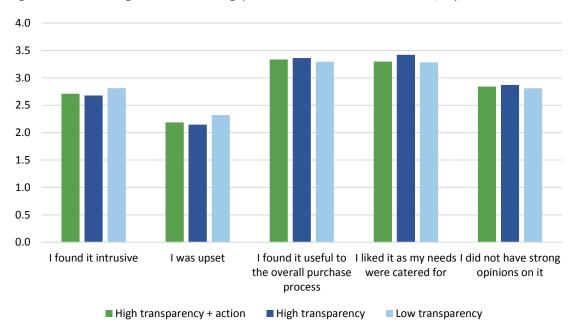


Figure 50: Feelings after realising personalisation had occurred, by treatment

Note: Question PP12a: "How did you feel after you realised you were seeing personalised results? Please select a number on the scale between 1 totally disagree and 5 totally agree for each statement." N=2,225.

Source: London Economics analysis of online experiment data

4.7.2. Participants' feelings about personalisation after being told about personalisation practices

Figure 51 shows the responses to the same statements, but for participants who did not realise personalisation occurred during the experiment, and were told about the personalisation within the post-experiment questions. These respondents tended to agree less with the positive statements (although they still realise the benefits of personalisation), and more with negative statements compared to participants who realised personalisation was occurring during the experiment. This may indicate that consumers are unhappy when they are not told upfront about personalisation practices, which may relate to issues related to trust online. The tables and figures in the next section explore the specific reasons for the scores given in this question.

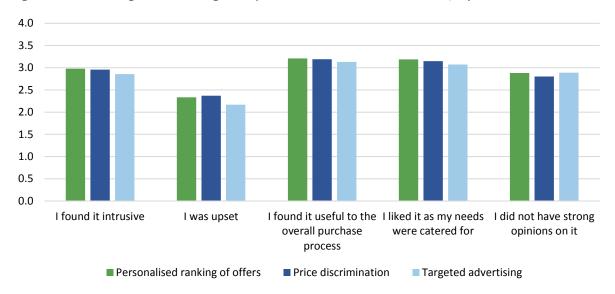


Figure 51: Feelings after being told personalisation had occurred, by scenario

Note: Question PP12b: "The results you were shown were personalised to you. How did you feel about this practice? Please select a number on the scale between 1 totally disagree and 5 totally agree for each statement." N=2,433.

Source: London Economics analysis of online experiment data

Similarly, participants tended to agree slightly more with negative statements, across treatments, when they were told about personalisation rather than realising it themselves. For example, the average score for the statement 'I found it intrusive' was 2.9 for participants in the high transparency plus action treatment when participants were told about personalisation, compared to 2.7 when participants realised that personalisation had occurred (Figure 50).

Participants also tended to report lower average agreement with negative statements in higher transparency treatments, compared to lower treatments. However the difference is small and not statistically significant.

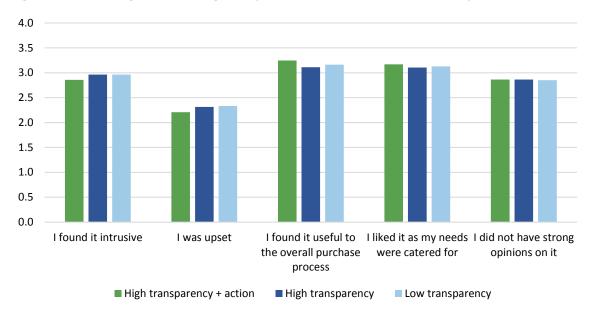


Figure 52: Feelings after being told personalisation had occurred, by treatment

Note: Question PP12b: "The results you were shown were personalised to you. How did you feel about this practice? Please select a number on the scale between 1 totally disagree and 5 totally agree for each statement." N=2,433.

Source: London Economics analysis of online experiment data

The behavioural experiment also assessed whether participants felt differently about personalisation depending on whether personalisation was based on search history, or browser/device. Participants who had experienced personalisation based on their search history were asked whether they would feel better or worse if personalisation was based on the device, and vice versa. In both cases, participants indicated their feelings on a scale from 1 to 5, where 1 was 'I would feel much worse' and 5 was 'I would feel much better'.

On average, participants indicated a response of approximately 3 in both cases. This suggests that participants were indifferent to whether personalisation was based on device/browser or previous search history.

Reasons behind participants' feelings about personalisation

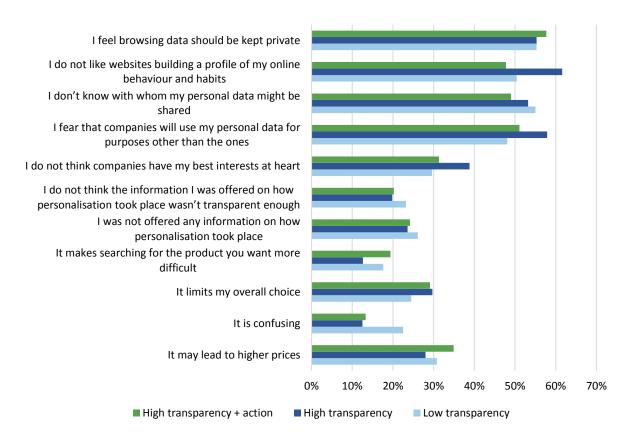
The post-experiment questionnaire examined the reasons behind the positive and negative feelings reported about online personalisation. Figure 53 to Figure 55 show the reasons for feeling negative about personalisation, by personalisation scenario. Across all scenarios the main reason for these feelings were:

- that browsing data should be kept private,
- participants do not like websites building profiles of their online behaviour and habits,
- concerns about with whom their personal data could be shared, and
- that companies could use the personal data of consumers for purposes other than the ones for which the data was gathered.

Across scenarios approximately half of all respondents selected each of the aforementioned reasons, with a slightly higher proportion selecting them in the personalised ranking of offers scenario. Reasons related to the transparency regarding personalisation or the amount of information provided about transparency appeared to be of a lower concern. Finally, concerns about higher prices or personalised inappropriate advertisements as a

result of personalisation were much less prominent, with between 20% and 40% of respondents selecting these reasons.

Figure 53: Reasons for feeling negative about personalised results, personalised ranking of offers scenario



Note: Question PP13a: "You indicated that you agreed with one or both of the following statements about the fact the results you saw were personalised (I find it intrusive, I was upset). Please explain why you feel this way. Please select all that apply" N=456.

Source: London Economics analysis of online experiment data

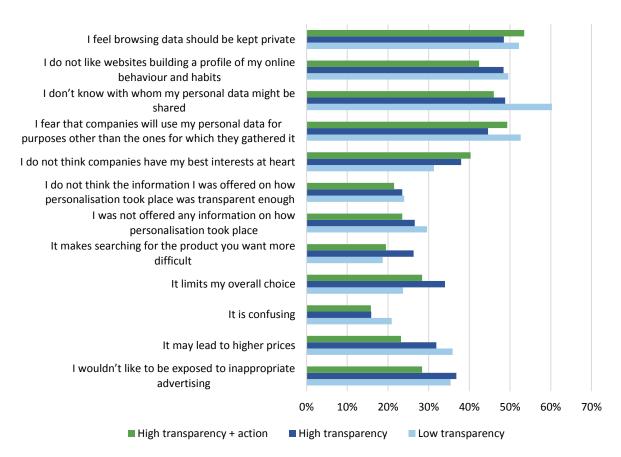
Figure 54: Reasons for feeling negative about personalised results, price discrimination scenario



Note: Question PP13a: "You indicated that you agreed with one or both of the following statements about the fact the results you saw were personalised (I find it intrusive, I was upset). Please explain why you feel this way. Please select all that apply" N=484.

Source: London Economics analysis of online experiment data

Figure 55: Reasons for feeling negative about personalised results, targeted advertising scenario



Note: Question PP13b: "You indicated that you agreed with one or both of the following statements about the fact the results you saw were personalised (I find it intrusive, I was upset). Please explain why you feel this way. Please select all that apply" N=425.

Source: London Economics analysis of online experiment data

Table 27 shows the results across scenarios for those respondents who reported positive feelings about personalisation. The most popular reasons for this positivity relate to the assistance that personalisation provides in the search process: 'Personalisation reduces the time I need to spend searching for the right product' was selected by approximately 60% of respondents, whereas 'Personalisation shows me more relevant products' and 'Personalisation allows me to more easily choose products that suit my needs' were selected by approximately 50% of respondents. Prices also seemed of lower relative importance, with less than 25% of respondents selecting the possibility of lower prices as a reason for their positive reaction to personalisation.

Table 27: Reasons for feeling positive about personalised results, by scenario and treatment

	Baseline	Low transparency	High transparency	High transparenc y + action	Across all treatm ents
	%	%	%	%	%
No personalisation					
Personalisation reduces the time I need to spend searching for the right product	60.3	-	-	-	60.3
Personalisation shows me more relevant products	56.3	-	-	-	56.3

	Baseline	Low transparency	High transparency	High transparenc y + action	Across all treatm ents
Personalisation allows me to more easily choose products that suit my needs	44.1	-	-	-	44.1
Personalisation makes searching more enjoyable	26.9	-	-	-	26.9
Personalisation allows e-commerce websites to offer me reductions/promotions	12.9	-	-	-	12.9
Personalisation could lead to lower prices	16.9	-	-	-	16.9
Personalised ranking of offers					
Personalisation reduces the time I need to spend searching for the right product	-	56.9	55.9	59.5	57.5
Personalisation shows me more relevant products	-	53.3	55.7	53.7	54.3
Personalisation allows me to more easily choose products that suit my needs	-	48.7	50.9	51.2	50.4
Personalisation makes searching more enjoyable	-	29.7	31.2	25.5	28.8
Personalisation allows e-commerce websites to offer me reductions/promotions	-	25.6	20.1	19.6	21.5
Personalisation could lead to lower prices	-	22.6	22.2	26.2	23.7
Price discrimination					
Personalisation reduces the time I need to spend searching for the right product	-	63.2	61.4	65.1	63.3
Personalisation shows me more relevant products	-	52.7	53.1	57.1	54.4
Personalisation allows me to more easily choose products that suit my needs	-	56.6	53.2	51.4	53.7
Personalisation makes searching more enjoyable	-	32.2	29.0	31.7	31.0
Personalisation allows e-commerce websites to offer me reductions/promotions	-	23.7	28.7	26.7	26.4
Personalisation could lead to lower prices	-	26.6	26.5	23.3	25.4
Targeted advertising					
Personalisation reduces the time I need to spend searching for the right product	-	61.9	57.8	67.2	62.2
Personalisation shows me more relevant products	-	56.0	44.0	57.1	52.0
Personalisation allows me to more easily choose products that suit my needs	-	53.1	51.0	53.0	52.3
Personalisation makes searching more enjoyable	-	27.0	24.1	23.3	24.7
Personalisation allows e-commerce websites to offer me reductions/promotions	-	26.2	17.2	21.8	21.5
Personalisation could lead to lower prices	-	24.3	24.8	18.7	22.6

Note: Question PP13c: "You indicated that you agreed with one or both of the following statements about the fact the results you saw were personalised (I find it useful to the overall purchasing process, I like it as my needs were catered for). Please explain why you feel this way. Please select all that apply" N=425.

Source: London Economics analysis of online experiment data

4.8. Usage of tools to prevent online personalisation and online behaviour

Do consumers use tools to prevent personalisation? To answer this question respondents were asked about the methods they use to protect their privacy when browsing the internet.

About four in ten (37% of) respondents indicated to always or very often use an "Adblocker"³⁸⁴. Slightly less than a third (30%) of respondents answered that they always or very often delete cookies³⁸⁵. The proportion of respondents who responded that they always or very often use the incognito/private mode of their browser was noticeably lower (18%), although close to two thirds (64%) of respondents indicated that they do use the incognito/private mode of their browser at least rarely. About one in ten (9%) of consumers indicated to always or very often use tools to hide their IP address, whilst a further 31% sometimes or rarely uses these tools. On the other hand, six in ten (60%) said to never use tools to hide their IP address or to not know about these tools. Slightly more consumers use "other plugins/apps designed to protect privacy online: 16% always or very often use these plugins/apps. On the other hand, slightly less than half (45%) never use these plugins/apps or don't know about them.³⁸⁶

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³⁸⁴ The reported ad-blocker usage appears high compared to 2016 figures from Eurostat, which showed that 'only' 17 % used the broader defined – although perhaps less concrete and well known – "anti-tracking software" ("software that limits the ability to track your activities on the internet"). However, apart from the differences in definition, it should be noted that the Eurostat figures: 1) refer to individuals who used the internet in the last year; 2) are collected by means of face-to-face interviews, telephone interviews and postal surveys (see methodological manual for "Statistics on the Information Society"). The current survey, on the other hand, targeted frequent internet users (those using internet once a week) and was carried out online, which could explain a somewhat more "tech savvy" sample. See for Eurostat figures: "Digital economy & society in the browse through our online world in figures", Eurostat http://ec.europa.eu/eurostat/cache/infographs/ict/images/pdf/pdf-digital-eurostat-2017.pdf

³⁸⁵ Eurostat figures from 2016 showed that slightly more than one third of internet users (35 %) in the EU had "changed their browser settings to prevent or limit the amount of cookies stored on their computer". Again this appears low compared to the findings from the current survey, in which 30% indicated that they always or very often delete cookies and a further 33% answered to do this "sometimes". However, it should be stressed that there are clear differences in definition (is changing your browser settings to "prevent or limit the amount of cookies stored" the same as deleting cookies?) and methodology that can explain the differences between the Eurostat data and the data from current survey. See note above for more details on the methodological differences and the link to the Eurostat data.

The same Eurostat report from 2017 included a number of other figures for actions internet users take to control personal information on the internet. For example, almost half of all internet users (46 %) in the EU did not allow the use of personal information for advertising purposes and 40 % limited the access to their profile or content on social networking sites. Other actions undertaken were reading privacy policy statements before providing personal information (37 %), checking that the website was secure (37 %), restricting access to geographical location (31 %) and requesting websites to update or delete personal information stored online (10 %). See "Digital economy & society in the EU. A browse through our online world in figures", Eurostat (2017). Link: http://ec.europa.eu/eurostat/cache/infographs/ict/images/pdf/pdf-digital-eurostat-2017.pdf

■ Always or very often ■ Sometimes ■ Rarely ■ Never ■ Don't know **EU28** Ad-blocker 37 9 Delete cookies 30 The incognito/private mode of my browser 11 Instruments to hide my IP address such as TOR, VPNs etc. 45 15 Other apps/plugins designed to protect privacy online 15 10 20 30 40 50 60 70 80 90 100

Figure 56: Methods to protect online privacy, frequency of use

 \overline{Q} 2. How often do you use the following methods to protect your online privacy when browsing the internet? %, EU28, Base: All respondents (n=21,734)

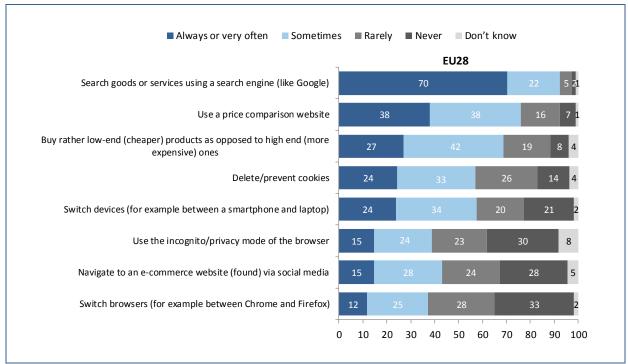
Source: Consumer survey

To measure how these tools are used in practice by consumers when shopping online, and to get a more general idea about consumers' online behaviour, respondents were asked which actions they undertake when searching and shopping online for goods or services.

Slightly less than a quarter of respondents (24%) indicated that they always or very often delete/prevent cookies when searching and shopping online for goods and services. About one in seven (15%) indicated to use the incognito/privacy mode of their browser always or very often when searching and shopping online for goods or services.

When looking at consumers' more general online behaviour when shopping online, we note that a large majority (70%) of respondents indicated that, when they search for goods and services, they always or very often use a search engine like Google. Close to four in ten (38% of) respondents responded that they always or very often use a price comparison website when searching and shopping online for goods or services. Slightly more than a quarter (27%) of respondents noted that, when buying online, they always or very often buy low-end/cheaper products rather than high-end/more expensive products.

Figure 57: Actions when searching and shopping online for goods or services



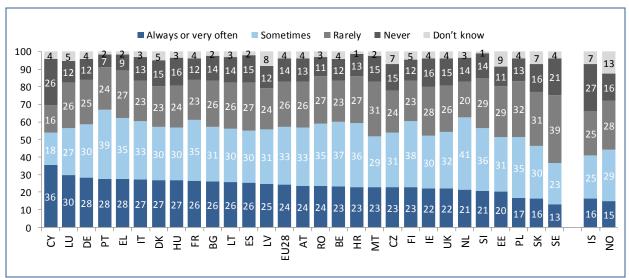
Q3. When searching and shopping online for goods or services, how often do you do the following?

%, EU28, Base: Respondents who bought goods or services online (n=20,704)

Source: Consumer survey

The proportion of respondents who always or very often delete cookies when searching and shopping online varies substantially across countries. Whilst in Cyprus 36% of respondents indicated that they always or very often delete cookies when searching and shopping online, in Sweden, this figure was just 13%.

Figure 58: Proportion or respondents who delete cookies when searching and shopping online, split by country



 $\overline{\text{Q3}}$. When searching and shopping online for goods or services, how often do you do the following? – Delete cookies

%, by country, Base: Respondents who bought goods or services online (EU28: n=20,704; NO: n=780; IS: n=477)

Source: Consumer survey

4.9. Knowledge about and experiences with cookies

As noted in section 3.1, cookies can play an important role in online personalisation. Moreover, although other methods for tracking users online, such as online fingerprinting and web beacons, are increasingly important (see the literature review), cookies remain undoubtedly the most familiar tracking technology among the general public. Hence, consumers' knowledge about cookies remains a relevant variable to measure the average consumer's understanding of online tracking and to look whether this is related to consumers' usage of methods and tools to prevent online tracking. More specifically, consumers' understanding of cookies may influence the way they deal with cookies when searching for goods and services online (i.e. whether they delete or block cookies, or not). Based on this hypothesis, respondents were presented with four statements about cookies. For each statement, respondents were asked whether they thought the statement was true or not.

- Cookies are small bits of code stored on your computer [Answer = true]
- Without cookies websites cannot know where I am located [Answer = false]
- Cookies can contain computer viruses [Answer = false]
- Cookies can read data saved on your computer [Answer = false]

In the chart below, we present the proportions of correct answers. "Don't know" was counted as incorrect. Roughly 7 in 10 respondents (71%) knew that cookies are small bits of code stored on a computer. This is in line with Eurostat figures which show that 71% of internet surfers aged 16-74 in the European Union (EU) know that cookies can be used to trace people on the internet³⁸⁷. In sharp contrast, however, only roughly a third (36%) of respondents were aware that also without cookies, websites can potentially still know where you are located. Only about a quarter (23%-25%) of respondents knew that cookies cannot contain computer viruses and cannot read data saved on a computer.

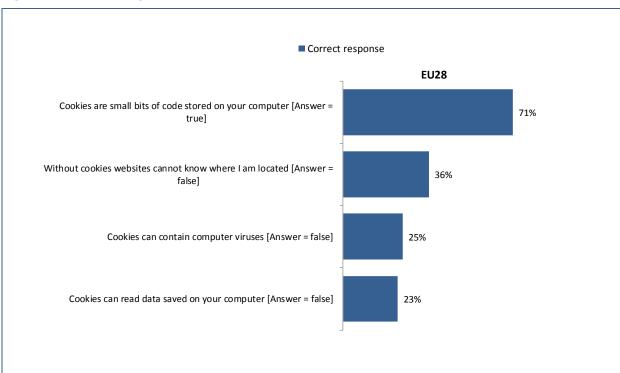


Figure 59: Knowledge about cookies

Q22. We present several statements about online "cookies". Please select whether each statement is true or false %, EU28, Base: All respondents (n=21,734)

Source: Consumer survey

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Source: Eurostat (2017), Safer Internet Day: cookies and your privacy. Link: http://ec.europa.eu/eurostat/web/products-eurostat-news/-/EDN-20170206-1

The proportion of respondents who answered correctly to all four knowledge questions about cookies was low in all countries, ranging from 8% in Ireland to 2% in Spain and Latvia. The proportion who answered 3 or 4 questions about cookies correctly ranged from 26% 388 in Malta to 13% in Latvia. At EU28 level, a little over half of respondents answered correctly either only one (35%) or even zero questions (17%).

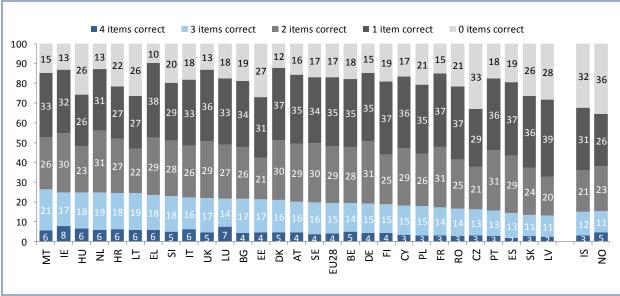


Figure 60: Knowledge about cookies, split by country

Q22. We present several statements about online "cookies". Please select whether each statement is true or false % (by number of correct responses), by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

The following table shows knowledge about cookies by socio-demographic variables in the EU28. Knowledge about cookies was higher for men; the average number of correctly answered statements about cookies was 1.73 for men, compared to 1.35 for women (the average number of correct responses across socio-demographic groups was 1.55, see rightmost column). Knowledge about cookies decreased somewhat with age; whilst the 16-34 age groups answered on average 1.59 questions correctly, this figure was 1.42 for the 65+ age group.

The number of correct responses varied more markedly by level of education. Whereas the least-educated answered, on average, 1.26 true/false statements correctly; this average was 1.70 for the highest educated. Those unemployed and looking or a job, and those unemployed and not looking for a job plus other non-actives, answered relatively fewer questions about cookies correctly (on average these socio-demographic groups answered 1.40 and 1.38 questions correctly, respectively, compared to for example on average 1.58 correct answers for the employed and 1.69 for the self-employed or students). Moreover, there appears to be a strong correlation about frequency of purchase and knowledge of cookies. Finally, the average number of correctly answered true/false statements about cookies ranged from 1.72 for those who indicated that making ends meet is "very easy" to 1.38 for those who said that meeting ends meet is "very difficult". EU15 respondents were also quite more likely to answer correctly compared to EU13 respondents.

³⁸⁸ 26% due to rounding (and not 27% as might be expected based on the figure); 5.52% of respondents had 4 items correct and 20.95% of respondents had 3 items correct in Malta.

Table 28: Knowledge about cookies, split by socio-demographic characteristics

	Base (EU28)	0 items correct	1 items correct	2 items correct	3 items correct	4 items correct	Average number of correct respons es
Average (EU28)	21,734	17%	35%	29%	15%	4%	1.55
EU Region							
EU15	11,832	15%	35%	29%		4%	1.57
EU13	9,902	23%	33%	25%	15%	4%	1.43
Age							
16-34	8,196	17%	33%	30%	17%	4%	1.59
35-54	9,170	17%	35%	28%		4%	1.54
55 – 64	2,992	17%	38%	27%		3%	1.50
65+	1,376	18%	40%	27%	12%	3%	1.42
Gender							
Male	10,959	12%	32%	31%	19%	6%	1.73
Female	10,775	22%	38%	27%	12%	2%	1.35
Working status							
Employed	12,413	16%	35%	29%		4%	1.58
Self-employed	1,713	14%	33%	29%	17%	7%	1.69
Unemployed but looking for a job	1,416	21%	37%	26%	13%	3%	1.40
Unemployed & not looking for a job + other non-active*	2.061	200/	200/	270/	120/	20/	1 20
· ·	3,961 2,231	20% 15%	38% 29%	27% 32%	12% 19%	2% 5%	1.38 1.69
Pupil / Student / In education Living area	2,231	15%	29%	32%	19%	5%	1.09
Large town or city	8,145	15%	34%	30%	16%	5%	1.60
Small or medium sized town	8,474	17%	35%	28%	15%	4%	1.53
Rural area or village	5,115	18%	35%	28%	16%	3%	1.50
Education	3,113	10/0	33/0	20/0	10/0	3/0	1.50
Low	2,250	23%	41%	24%	10%	2%	1.26
Medium	9,506	19%	35%	28%	14%	4%	1.49
High	9,978	13%	33%	31%	18%	5%	1.70
Household financial situation	3,3.0	20,0	33,1	01/0	20,0	2,0	20
Very easy	1,727	14%	31%	31%	19%	6%	1.72
Fairly easy	9,277	15%	33%	30%	17%	5%	1.64
Fairly difficult	7,953	18%	37%	28%	14%	3%	1.48
Very difficult	1,988	20%	41%	25%	11%	4%	1.38
Frequency of purchasing products online	·						
Once a week or more often	4,944	14%	33%	30%	19%	5%	1.68
Once a month or more often	8,500	15%	35%	30%	16%	5%	1.62
Once every 3 months or more							
often	4,943	19%	37%	28%	12%	3%	1.44
Once in the last 12 months or							
more often	2,317	25%	37%	24%	13%	2%	1.29
Never	1,030	36%	31%	22%	10%	1%	1.10
*Sick/disabled, Housewife/homem	aker, Retired	1					

Q22. We present several statements about online "cookies". Please select whether each statement is true or false % (by number of correct responses), EU28, Base: All respondents (n=21,734)

Source: Consumer survey

Is there a correlation between respondents' knowledge about cookies and respondents' usage of methods to protect their online privacy? The table below suggests that this is – to some degree – the case. Respondents who answered three to four of the questions about cookies correctly, were over-represented in the group who always or very often use an ad-blocker, especially when compared to those respondents who answered zero questions about cookies correctly. Respondents who answered three to four of the questions about cookies correctly were also more likely than those who answered zero questions about cookies correctly to always/very often or sometimes delete cookies or use the incognito/private mode of the browser. For example, whilst 52% of respondents who answered 3-4 questions about cookies correctly at least sometimes use the incognito/private mode of their browser, this figure is just 31% for respondents who answered 0 questions about cookies correctly.

Table 29: Methods to protect online privacy, split by knowledge about cookies

	Base (EU28)	Average (EU28)	0 items correct	1-2 items correct	3-4 items correct				
Use: Ad-blocker									
Always or very often	8,399	37%	24%	38%	47%				
Sometimes	3,821	17%	16%	18%	16%				
Rarely or never	7,825	37%	41%	37%	33%				
Don't know	1,689	9%	19%	7%	3%				
Use: The incognito/p	orivate mo	de of my	browser						
Always or very often	4,271	18%	13%	19%	20%				
Sometimes	5,428	24%	19%	24%	32%				
Rarely or never	9,645	46%	45%	47%	44%				
Don't know	2,390	11%	24%	10%	4%				
Delete cookies									
Always or very often	6,510	30%	21%	33%	31%				
Sometimes	6,951	33%	26%	33%	37%				
Rarely or never	7,182	32%	38%	31%	31%				
Don't know	1,091	5%	14%	3%	1%				

Q2. How often do you use the following methods to protect your online privacy when browsing the internet? & Q22. We present several statements about online "cookies". Please select whether each statement is true or false % (by number of correct responses), EU28, Base: All respondents (n=21,734)

Source: Consumer survey

Cookies that can track online behaviour do not only play a potentially important role in online personalisation, but are also subject to EU law³⁹⁰. For this reason, the consumer survey included questions to research whether, in practice, consumers are always able to refuse cookies and if they make use of this option, if available.

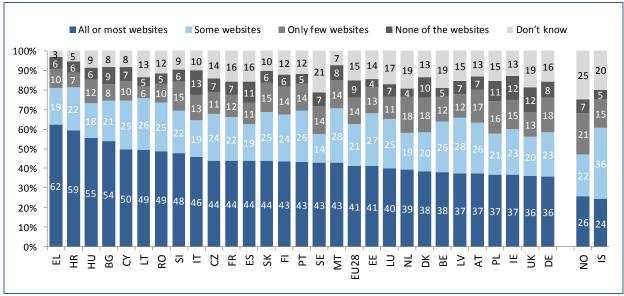
Across the EU28, four in ten (41% of) respondents indicated that in their experience, all or most websites offer the possibility to refuse cookies. Roughly a third (35%) of EU28 respondents reported that in their experience just some or only a few websites allow to refuse cookies. A further 9% mentioned that none of the websites provide this option. Roughly one in seven (15%) of respondents did not provide an answer.

³⁸⁹ The correct figure is 31% (and not 32%), due to rounding.

³⁹⁰ Article 5(3) of the ePrivacy Directive provides that the storing of information, or the gaining of access to information already stored in the terminal equipment is only allowed with the consent of the user.

At country level, substantial differences can be perceived. On one end of the country scale, in Greece, more than six out of ten (62%) respondents reported that in their experience most or all websites allow to refuse cookies. On the other end of the scale, in Germany and the UK, just 36% of respondents reported that in their impression websites tend to allow to /refuse cookies. Other countries where half or more respondents reported that all or most websites allow to refuse cookies are Croatia (59%), Hungary (55%), Bulgaria (54%) and Cyprus (50%).

Figure 61: Respondents' impressions of the proportion of websites that allow to refuse cookies, split by country



Q23. Approximately how many websites that you visit allow to "opt-out of"/refuse cookies? %, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

In the mystery shopping exercise for this study, shoppers were asked to indicate in the evaluation form if the website they visited had informed them about the usage of cookies and whether they had been offered the possibility to refuse cookies³⁹¹. As can be noted in table below, for slightly less than two third (64%) of the mystery shopping visits, shoppers indicated that they were in some way informed about the usage of cookies. In less than a quarter (22%) of the mystery shopping visits, however, it was possible to refuse cookies, as reported by the shoppers.

sufficient to provide valid consent (WP 208). Thus, while consent is required for the storage or access to cookies, the questionnaire also inquires about opt-out mechanisms to obtain knowledge about the observations and behaviour of interviewees in practice.

³⁹¹ The Article 29 Working Party observes that although Article 5.3 of the ePrivacy Directive stipulates the need for consent for the storage of or access to cookies, the practical implementations of the legal requirements vary among website operators across EU Member States. It observes that not all implementations may be

Table 30: Proportion of websites that provide information about and/or allow to refuse cookies, findings from the mystery shopping

	% of websites
Yes, and I was offered the possibility to 'opt out' of/refuse cookies	22%
Yes, but I was not offered the possibility to 'opt out of'/refuse cookies (I had to accept to continue navigating)	16%
Yes, but it was possible to navigate through the website without having to accept cookies	26%
No, I did not see a cookie policy	36%

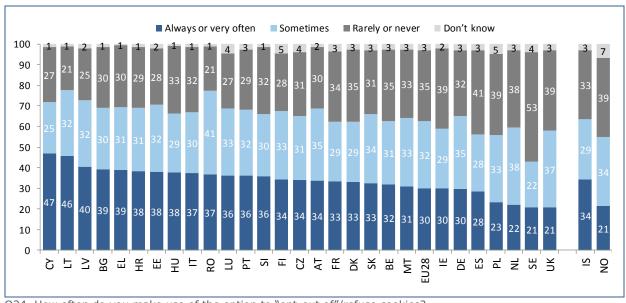
E3. Did you see a cookie policy informing you that the website uses cookies and were you offered the possibility to opt out of the use of cookies? Select all that apply.

%, by website, Base: n=717 shops (on 160 websites)

Source: Mystery shopping exercise

All respondents in the consumer survey who indicated that a few to all websites allow to refuse cookies, were also asked whether they make use of that option. Across the EU28, slightly less than a third (30%) of respondents indicated that they always or very often make use of the option to refuse cookies. Similar proportions across the EU28 reported that they "sometimes" (32%) or "rarely/never" (35%) refuse cookies. The proportion of respondents who indicated that they always or very often make use of the option to refuse cookies ranged from 47% in Cyprus to 21% in Sweden and the UK. The socio-demographic profile of respondents who use the option to refuse cookies does not show a lot of variation (see Annex A4.2).

Figure 62: Respondents' use of the option to refuse cookies, split by country



Q24. How often do you make use of the option to "opt-out of"/refuse cookies?

%, by country, Base: All respondents who indicated that a few or more websites allow to "opt-out/refuse cookies (EU28: n=17,276; NO: n=551; IS: n=382)

Source: Consumer survey

4.10. Summary of results – Consumers' awareness and perception of personalised pricing/offers and problems reported

In the box below the key findings of this chapter are summarised.

Box 3: Summary of findings – Consumers' awareness and perception of personalised pricing/offers and problems reported

Consumers' awareness of personalised practices

- In the consumer survey, the self-reported awareness about online personalised pricing was lower than the self-reported awareness about online targeted adverts and personalised ranking of offers. At EU level, 67% of respondents indicated that they understood or had some understanding of targeted adverts. For personalised ranking of offers the comparable figure was 62%, for personalised pricing this was 44% only.
- The results from the consumer survey and the behavioural experiment suggest that potentially vulnerable consumers, such as older people, those with low educational attainment, those having difficulty making ends meet, or those inexperienced with online shopping, report lower awareness of personalisation. For example, in the behavioural experiment 38% of participants with low educational attainment reported awareness of personalisation when asked whether the search results they were seeing had been personalised, compared to 46% of other participants. Moreover, only 36% of respondents aged 65+ reported similarly, as opposed to 49% of respondents aged 16-34.
- In the behavioural experiment, participants were significantly more likely to report awareness of personalised ranking of offers if they received transparent communication about personalisation practices from the online platform. For example, 39% of participants in the high transparency treatment (where they received more transparent communication informing them that the product was recommended to them based on their previous searches) reported awareness of personalised ranking of offers, compared to 29% in the low transparency treatment (in which they were *not* informed that the product was personalised to them).
- In the behavioural experiment, in many cases, a significantly higher proportion of potentially vulnerable participants reported awareness of personalisation when the online platform was more transparent in its communication that the product was recommended to them based on their previous searches. For example, 39% of economically inactive participants reported awareness of personalisation in the "low transparency treatment" of the behavioural experiment. But this proportion increased to 46% in the higher transparency treatments in which they were informed that the product was recommended to them based on their previous searches. Similarly, 34% of participants with low education reported awareness of personalisation practices in the low transparency treatment of the experiment, rising to approximately 44% in the highest transparency treatment. With older respondents (65+) this was even more striking (28% in the low transparency treatment to 44% in the highest transparency treatment).
- Self-declared awareness does not necessarily imply that consumers recognise online personalised practices when confronted with them: In the behavioural experiment the proportion of respondents that correctly identified online targeted adverts or personalised ranking of offers/pricing when these occurred was <50% for all these practices and for all levels of communication transparency. The ability to identify personalised pricing was especially low: less than 20% of participants in the behavioural experiment correctly identified price personalisation when they experienced prices which were lowered based on the participants' previous search history.</p>
- In the behavioural experiment, respondents allocated to the high communication transparency treatment and the high communication transparency + action

treatment (in which participants received the most salient communication of personalisation, and it was easier for them to clear cookies and search again) correctly identified *personalised ranking of offers* significantly more often than those allocated to the low transparency treatment (41.4% and 38.6% against 28.9%). However, there was very little difference in the proportion of respondents correctly answering whether they have experienced personalised pricing or targeted advertising, as transparency in the communication increased.

Perceived benefits and concerns

- Respondents in the consumer survey cited as their three main *benefits* of:
 - Targeted adverts: allowing to see interesting products (42%); reducing number of irrelevant adverts (23%); and funding free content (20%).
 - Personalised ranking of offers: allowing to see interesting products (34%); saving time when searching online (23%); and making it easy to choose products that suits consumers' needs (23%).
 - Personalised pricing: allowing e-commerce websites to offer reductions/promotions (22%); allowing to get the best available price for products (21%); and allowing to increase product choice (15%).
- The share of respondents who did not perceive any benefits ranged from 24% for targeted adverts, to 25% for personalised ranking of offers, and 32% for personalised pricing.
- Compared to respondents in the EU13, respondents in the EU15 were more likely *not* to perceive any benefits of the three online personalisation practices.
- Respondents in the consumer survey cited as their three main concerns with respect to:
 - Targeted adverts: their personal data could be used for other purposes and/or shared with others/3rd parties (49%); their online data being collected/ a profile being made about them (46%); and cookies being installed on their computer (27%).
 - Personalised ranking of offers: their personal data could be used for other purposes and/or shared with others/3rd parties (46%); their online data being collected/ a profile being made about them (42%); and cookies being installed on their computer (25%).
 - Personalised pricing: their personal data could be used for other purposes and/or shared with others/3rd parties (36%); their online data being collected/ a profile being made about them (33%); and them ending up paying more (28%).
- Approximately 50% of behavioural experiment respondents who reported negative feelings about personalisation indicated that they felt their browsing data should be private, not liking websites to build a profile of their online behaviour and not knowing with whom their personal data might be shared.
- For each of the three personalisation practices, less than one in ten respondents indicated not to have any concerns. This figure varied from 7% for online targeted adverts and online personalised pricing, to 9% for online personalised ranking of offers.
- The proportion of respondents without any concerns about the three online personalisation practices was on average significantly higher in EU13 countries compared to EU15 countries.
- A substantial proportion of respondents (16%-25%, depending on the online personalisation practice) indicated as one of their three main concerns that they cannot refuse or "opt-out".

Experiences & complaints

• The proportion of all respondents who had bad experiences with the applicable personalised practice was 18% for online targeted adverts, 14% for online personalised ranking of offers, and less so (12%) for online personalised pricing.

- The proportion of respondents who had bad experiences was somewhat higher for respondents who indicated to be aware of the applicable online personalisation practices. Notably, of those respondents who indicated to understand or have some understanding of personalised pricing, a fifth (20%) indicated to have had bad experiences with this practice (compared to 12% of all respondents who said to have had bad experiences with personalised pricing). Hence, there appears to be a relation between awareness and the number of bad experiences reported.
- In Finland, Hungary and Denmark, across all 3 personalisation practices, a much higher proportion of respondents reported bad experiences.
- The most frequently reported bad experience was having been offered a product not or no longer interested in: of the quarter (25%) of respondents who reported to have had a bad experience with one of the 3 online personalisation practices, half (50%) reported having been offered such an unwanted product.
- Slightly more than a quarter (27%) of respondents who reported a bad experience with one or more of the 3 online personalisation practices indicated that they ended up paying more for something they bought
- Almost three quarters (73%) of respondents who experienced a problem with personalised practices did not file a complaint. If respondents did complain, they did so most often to the website (10%) or to national consumer organisations (6%). The proportion of respondents complaining ranged from 52% in Croatia to 14% in the Netherlands.
- The CPA and DPA stakeholders supported that they do not frequently receive many complaints about online personalised practices.

Overall opinion on personalised practices

- Approximately half of respondents in the consumer survey saw both disadvantages and advantages for either targeted adverts or personalised ranking of offers, whereas this was the case with only 1 in 3 respondents for personalised pricing. The share of respondents who saw disadvantages only ranged from 29% for targeted advertising to 28% for personalised ranking of offers to 33% for personalised pricing. The corresponding percentages for respondents who saw only benefits were between 8-9% respectively.
- In general, participants in the behavioural experiment tended to agree more with positive statements about their feelings towards personalisation (e.g. finding it useful to the overall process) compared to negative statements (e.g. finding it intrusive).
- About six in ten (62%) respondents in the consumer survey said that they would be more positive about online personalised practices if there would be an easy option to "opt-out". More than half (55%) of respondents said they would be more positive when it would be explained what personal data is collected and when they could see and change this data. The behavioural experiment confirmed that consumers are unhappy when they are not told upfront about personalisation practices.

Usage of tools to prevent personalisation

- Slightly less than a third (30%) of respondents answered that they always or very often delete cookies, whereas 63% have reported to at least rarely use the incognito mode in order to protect their privacy when searching online.
- Six in ten (60%) respondents said to never use tools to hide their IP address or to don't know about these tools. Slightly less than half (45%) of respondents never use other plugins/apps designed to protect privacy online or don't know about them. The proportion of respondents who always or very often use these tools is 9% for tools to hide the IP address and 16% for other plugins/apps.

Knowledge about and experiences with cookies

 Because cookies remain the online tracking method most well-known to the general public (contrary to for example digital fingerprinting) and because consumers' understanding of cookies may tell something about the average consumers'

- knowledge about online tracking and online behaviour, respondents in the consumer survey were asked about their knowledge and experience with cookies.
- Overall knowledge of cookies appeared to be fairly low: On average respondents answered 1.55 out of 4 questions about cookies correctly.
- Respondents with a good knowledge of cookies appear somewhat more likely than respondents with a bad knowledge of cookies to protect their privacy online. For example, whilst 52% of respondents who answered 3-4 questions about cookies correctly at least sometimes use the incognito/private mode of their browser, this figure is just 31% for respondents who answered 0 questions about cookies correctly.
- Across the EU28, four in ten (41% of) consumer survey respondents indicated that in their experience, all or most websites offer the possibility to refuse cookies. In the mystery shopping exercise, in less than a quarter (22%) of the mystery shopping visits it was possible to actually refuse cookies, as reported by the shoppers.

5. Research on the incidence and magnitude of online personalised pricing/offers

This chapter uses the mystery shopping data to look for objective evidence of offer ranking and price personalisation used by e-commerce websites. This is supplemented with findings from the consumer and stakeholder surveys on the perceived/ subjective incidence and magnitude of online personalised pricing/offers.

5.1. Personalised practices encountered by mystery shoppers

Section 5.1.1 analyses product offers and the order in which products appear in e-commerce websites. It finds evidence of offer ranking personalisation both based on information about the shopper's past online behaviour (cookies, search history etc.) as well as on information about the shopper's access route to the website (search engine referral, Price Comparison Website referral, browser used, device used...).

Access through a Price Comparison Website (PCW) or using a mobile device is shown to have the strongest impact on the ranking of product offers. The evidence is robust across most countries and product categories. In particular, the research found that Polish, Swedish, British and Romanian e-commerce websites had the most offer ranking personalisation. German, Czech, Spanish and French websites exhibited lower offer ranking personalisation, sometimes not statistically recognisable from random noise. Among product categories, airline ticket and hotel offers emerged as the most personalised, while sport shoes and TVs as the least. These results appear consistently across all scenarios considered.

When interpreting the mystery shopping, it is important to note that the results are based on a (non-random) sample of 160 websites across 4 product categories and 8 EU Member States³⁹². They are not necessarily representative of EU e-commerce as a whole. Annex A1.6 summarises the methodology underlying the mystery shopping data collection exercise and how the specific sites included in the mystery shopping where selected. When it comes to airline tickets, websites of platforms selling air tickets were assessed and not those of airline companies themselves.

Section 5.1.2 focuses on **price personalisation**, exploring whether shoppers pay more or less for identical products when their personal characteristics are observable (either past online behaviour or access route to the website). In 94% of the matched product pairs, there was no price difference at all. Among the remaining 6% of product pairs where some price difference was recorded, the median price difference (in absolute values) was less than 1.6%. The analysis found absolute price differences that could not be explained entirely by random price variation, but they are in most cases very small in magnitude and relatively evenly distributed around zero. This leads to statistically insignificant net price differences. The analysis based on the mystery shopping data therefore did not find evidence of consistent and systematic price differences between scenarios where the e-commerce website could observe shopper characteristics and when it could not. The few statistically significant differences found are very small in magnitude and specific to a country or product category. Larger differences were found when comparing different personalisation scenarios with each other than when comparing the scenarios to a control **shop**³⁹³. In particular, in some countries, access to the website through a PCW is linked

393 In the control shop, mystery shoppers recorded product offers and prices while preventing the e-commerce websites from tracking them. The researchers took measures to prevent the websites from observing their search engine, browser, cookies, browsing/search history, IP address, browser fingerprints etc.

³⁹² The sample includes retailer websites as well as some online marketplaces. However, the sample size does not allow extracting robust evidence about the two categories separately.

with a price difference of up to 3% on average compared to direct URL access or access through a search engine query.

Finally, the chapter considers the combined effect of price and offer ranking personalisation by comparing prices of top-ranked products between situations with different shopper characteristics observable to the sellers. **Overall the analysis based on the mystery shopping data doesn't find evidence of systematic price differences of top-ranked products**; nevertheless, **some statistically significant but small results are found at the level of individual product categories**. Access from a mobile device is linked to more expensive airline tickets, but cheaper sport shoes and TVs. Cheaper top-ranked TVs and more expensive airline tickets than in the control shop are also observed when the website is accessed directly by URL access, but the effect is very small.

5.1.1. Personalised offers

This section assesses personalised offers encountered by mystery shoppers i.e. how often mystery shoppers were shown different ranking of products, depending on the personal characteristics sellers could observe.

Offer personalisation is quantified using a similarity index taking values from 0 to 1^{394} . The index is the product of two components:

- The share of common products between two situations e.g. if 3 out of the top 5 ranked products are the same between scenario A and the control shop, this component would take the value 3/5;
- The share of common products that also appear in the same rank order e.g. if 2 out of the 3 common products had the same rank order between scenario A and the control shop, this component would take the value 2/3;
- Therefore, in this example, the similarity index would take the value (3/5)*(2/3)=6/15

Note that the number of common products appears both in the numerator of the first fraction and the denominator of the second fraction. Mathematically, this implies that this value cancels out. Therefore, in practice, the index is the number of products that appear in the same rank order divided by the number of observed products. In the example above, the similarity index = 2/5 = 6/15.

A lower similarity index indicates greater offer personalisation. An index value of 1 means that the compared product offers are exactly identical, both in the products they feature and the order in which these products are shown. An index value of 0 means that the shoppers did not observe any common products that also appeared in the same rank order.

Therefore, in theory, if two mystery shoppers carried out identical shopping exercises, the similarity index should be equal to 1. However, in practice, the analysis needs to account for random variation in e-commerce results, leading to similarity indices lower than 1 for even identical mystery shops. This variation can arise for example from websites' A/B testing or dynamic pricing.

Therefore, in order to assess significant offer personalisation, the study carries out the following procedure:

Construct a baseline index where variation is random. This is done by computing
the similarity index for identical steps in the mystery shopping exercise (see Table
31 and the Annex for further details on construction of the baseline index);

³⁹⁴ See the Annex for further details on the construction of the index. The Annex also presents an alternative index to illustrate robustness of the results to index choice. The choice of similarity index does not have a substantial impact on the share of websites personalising offers, either overall, or by product, country or scenario.

Compare the similarity index between two situations with the baseline index.³⁹⁵

Therefore, if the similarity index between e.g. scenario B and the control shop is statistically significantly lower than the baseline index, we can argue that the difference cannot be entirely explained by random variation (i.e. variation that is not due to personalisation).

This section presents both the similarity index as well as the share of websites that personalise their offers. A website is defined as personalising the ranking of offers if the average similarity index of the website is at least 10% lower than the website's baseline index. The However, the results are similar if the cutoff is 5% or 20% i.e. a website is defined as offer-personalising if its average similarity index is 5%, or 20% lower than the baseline index. The Annex presents a detailed sensitivity analysis illustrating the robustness of the offer-personalising results to the assumption of the cutoff.

The following sections describe offer ranking personalisation at a number of levels:

- Mystery shopping scenarios relative to the control shop;
- Mystery shopping scenarios relative to the control step;
- Mystery shopping scenarios relative to each other;
- Disaggregated by product and country

The mystery shopping data also allows us to assess the impact of different types of personalisation on offers and prices.

Table 31 summarises the shopper characteristics that sellers can observe in different steps of the mystery shopping exercise, and therefore the types of personalisation we can use the data to analyse.

For example, in step A1 of the mystery shopping exercise, sellers can observe the shopper's preferred browser and search engine, as well as browsing history, since cookies are not disabled.

In Step A3, sellers can continue to observe the shopper's browser and search engine, but cookies are disabled (with the use of incognito browsing) so sellers cannot observe the shopper's browsing or search history. Therefore, comparing step A1 with A3 allows us to examine the impact on offers/prices of cookies and potentially browsing or searching history that the browser or search engine provided to the e-commerce website.

In step C1, sellers can observe the shopper's browser. Step C3 is identical except shoppers switch to an alternative browser. In both steps, cookies are not disabled and sellers can observe the shopper's browsing history. Therefore, comparing steps C1 and C3 allows us to assess the impact of personalisation based on browser, when sellers can observe browsing history.

396 This approach is used to define an offer-personalising website, because the analysis cannot perform statistical testing since only 4-6 shops were conducted per website. If due to data unavailability the website's baseline index cannot be calculated, we instead use the baseline index for the product category. More details on our methodological choices can be found in the Annex.

³⁹⁵ The similarity index between two situations is the unweighted average of the similarity indices observed in individual shops in our sample. As a robustness check, we also calculated averages weighted by the traffic of the website on which the shop was conducted. The weighting did not significantly influence the results.

Table 31: Overview of characteristics observable to e-commerce website in different scenarios

Step	Browser	Search engine	Direct website visit	PCW referral	Mobile device	Cookies/ browsing history	Comments
Control shop	No	No	No	No	No	No	Also IP address and canvas fingerprinting tracking blocked. ³⁹⁷
A1	Yes	Yes*	No	No	No	Yes	*Preferred search engine
A2	Yes	Yes*	No	No	No	Yes	*Search engine that doesn't track users
А3	Yes	Yes*	No	No	No	No	*Preferred search engine
A4	Yes	Yes	No	No	No	No	Repeats A3
B1	Yes	No	No	Yes	No	Yes	
B2	Yes	No	Yes	No	No	No	
C1	Yes*	No	Yes	No	No	Yes	*Preferred browser
C2	Yes*	No	Yes	No	No	No	*Preferred browser
С3	Yes*	No	Yes	No	No	Yes	*Alternative browser
C4	Yes*	No	Yes	No	No	No	*Alternative browser
D1	Yes	No	Yes	No	Yes	Yes	
D2	Yes	No	Yes	No	Yes	No	
D3	Yes	No	Yes	No	Yes	No	Repeats D2

Note: Mystery shoppers are using their preferred browser/search engine unless specifically stated.

Source: London Economics

Offer personalisation compared to control shops

Table 32 shows the average similarity indices between the steps where some characteristics of the shopper were observable and the control shops, in which the ecommerce website couldn't access any information about the shopper. The table also shows the proportion of the websites in our sample whose average similarity index relative to the control shop would indicate that they personalise offers.

³⁹⁷ Annex A1.6 provides more details about the setup of the control shop.

In all cases, the similarity index is significantly lower (at 99.9% confidence level) than the baseline index. This means that the differences between the steps are not due to random noise, and could be more likely due to personalisation. Over three fifths of e-commerce websites (61%) are found to personalise offers in **at least** one scenario – i.e. over three-fifths of websites personalise offers through search engines **or** PCWs **or** browser **or** mobile devices. Analysing at the level of individual mystery shopping steps, the share of personalising websites ranges from 38% in C1 to 48% in C2 (see Table 32).

The lowest index – indicating greatest offer personalisation – is recorded in scenario D, in which shoppers used their mobile devices (phones, tablets) rather than personal computers. This is in line with previous literature suggesting that e.g. Android users were shown costlier products (IB Times, 2014)³⁹⁸.

The index is also particularly low in scenario B, in which shoppers accessed the e-commerce website through a price comparison website (PCW).

Table 32: Offer personalisation by type of characteristics observable: average across countries and products – comparison with the control shop

Scenario	Step compared with the control shop	Baseline index	Average similarity index	Share of websites that personalise offers
Any	Any			61%
	A1	0.95	0.80***	40%
Search engine	A2	0.95	0.78***	40%
	A3	0.95	0.80***	39%
PCW	B1	0.95	0.78***	41%
	B2	0.95	0.78***	43%
	C1	0.95	0.79***	38%
Browser	C2	0.95	0.76***	48%
2.0	C3	0.95	0.78***	41%
	C4	0.95	0.78***	42%
Mobile	D1	0.94	0.76***	42%
device	D2	0.94	0.76***	41%

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample size: 464-635 shops, 141-152 websites (varies by step)
Source: London Economics analysis of mystery shopping data

In some cases, however, we see results that are more difficult to interpret.

In general, we would expect the control steps (A2, A3, B2, C2, C4, D2) to be more similar to the control shops than the steps with greater extent of personalisation (A1, B1, C1...). However, the similarity indices indicate that there is either no difference or that the control

³⁹⁸ IB Times (2014), <u>Mac and Android Users Charged More on Shopping Sites Than iPhone and Windows Users</u>

steps are in fact less similar to the control shops. This may seem surprising, however, the result is usually not statistically significant.

Offer personalisation compared to control shops – by products and countries

The finding that offer personalisation is greatest in Scenario B (PCW) and Scenario D (mobile device), as evidenced by the lower similarity indices, is consistent across most product categories and Member States.

However, breaking down the results by product category reveals considerable differences between sectors (see Table 33). In all personalisation scenarios, airline tickets exhibit the largest degree of offer personalisation (relative to the control shop), with the similarity index for airline tickets ranging from 0.61 (mobile device) to 0.66 (browser). Hotels are the second most personalised category, with indices between 0.63 (PCW) and 0.75 (browser). By contrast, the similarity index for sport shoes is high, ranging from 0.85 (mobile device) to 0.89 (PCW). TV offers are the least personalised, but still statistically significantly lower than the baseline index (random noise). 399

Table 33: Offer personalisation by product

Product	Baseline Index: desktop/ laptop	Search engine Index: (A1)	Price Comparison Website Index: (B1)	Internet browser Index: (C1)	Baseline Index: mobile device	Mobile device Index:(D 1)
Airline ticket	.88	0.64***	0.62***	0.66***	.87	0.61***
Hotel	.94	0.74***	0.63***	0.75***	.94	0.70***
Sport shoes	.99	0.88***	0.89***	0.88***	.98	0.85***
TV	.99	0.93***	0.91***	0.87***	.97	0.87***

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample size: 96-168 shops (varies by product and scenario)

Source: London Economics analysis of mystery shopping data

Differences in offer personalisation between sectors are observed systematically across websites i.e. the differences between sectors are not driven by a small number of outlier websites. In the airline ticket sector, 92% of websites personalise their offers in at least one of the mystery shopping scenarios. The share of personalising websites is 76% of websites in the hotel sector, 41% in sports shoes, and 36% in TVs. Table 34 shows shares of websites that personalise offers by scenario.

³⁹⁹ The following two tables present a comparison of steps A1, B1, C1 and D1 (vs the control shop) with the baseline index. We do not present the full set of comparisons of mystery shopping steps compared to the baseline index, since they follow a similar pattern.

Table 34: Share of websites that personalise offers, by product category

Product	Any scenario	Search engine (A1)	Price Comparison Website (B1)	Internet browser (C1)	Mobile device (D1)
Airline ticket	92%	78%	71%	73%	76%
Hotel	76%	42%	55%	39%	50%
Sport shoes	41%	28%	25%	23%	23%
TV	36%	15%	18%	21%	21%

Note: A website is considered to be offer-personalising if its similarity index relative to the control shop is at least 10% smaller than the website's baseline index. For results using 5% and 20% threshold, please see the Annex. Sample size: 33-39 websites (varies by scenario and product category)

Source: London Economics analysis of mystery shopping data

At the level of individual countries, differences are also notable and consistent across personalisation scenarios (see Table 35). Polish, Swedish, British and Romanian ecommerce websites were the Member States with the lowest similarity indices (therefore the most significant offer personalisation), while German, Czech, Spanish and French websites had the lowest offer personalisation. In Germany and the Czech Republic, offer variation is often not significantly different from random noise. Note, we have no information as to why this may be the case, but will review if there is information from Task 1 which could help to shed light on this.

Table 35 : Offer personalisation by country

Product	Baseline desktop/ laptop	Search engine (A1)	Price Comparison Website (B1)	Internet browser (C1)	Baseline mobile device	Mobile device (D1)
Czech Republic	0.93	0.90	0.91	0.87*	0.98	0.87***
France	0.92	0.85*	0.66***	0.85*	0.93	0.83**
Germany	0.97	0.94*	0.92	0.89**	0.92	0.88
Poland	0.94	0.62***	0.67***	0.61***	0.90	0.58***
Romania	0.99	0.80***	0.79***	0.78***	0.98	0.80***
Spain	0.98	0.84***	0.88**	0.88***	0.97	0.90**
Sweden	0.93	0.70***	0.63***	0.67***	0.92	0.62***
United Kingdom	0.98	0.78***	0.77***	0.81***	0.95	0.68***

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample size: 44-85 shops (varies by country and scenario)

Source: London Economics analysis of mystery shopping data

Results for the share of offer-personalising websites show a similar pattern – that is, Member States with higher average similarity indices relative to the baseline also tend to have the smallest share of offer-personalising websites.

For example, in Germany and the Czech Republic, where there was least significant evidence of offer personalisation, 42% and 47% of websites respectively personalise offers in at least one of the scenarios. By contrast, in the UK, Sweden, and Poland, where the data suggest more systematic offer personalisation, the respective shares are 65%, 75% and 79%. In these countries, the results suggest that the recorded low or high similarity

indices reflect a broad pattern of market behaviour employed by the majority of the websites.

By contrast, in the case of Romania and France, the results suggest that the extent of offer personalisation is driven by a smaller share of websites.

For example, Romania's average similarity index was relatively low i.e. the average level of offer personalisation was relatively high. However, this result is driven by only 47% of websites that personalise their offers in at least one of the scenarios.

In France, by contrast, we may expect the average offer personalisation to be relatively high since 70% of the e-commerce websites in the sample identified as personalising in at least one of the scenarios. However, the similarity indices of the mystery shopping scenarios are relatively high compared to the baseline (see Table 32) – that is, average offer personalisation in France is relatively low.

In the case of France, this apparently counterintuitive result seems to be driven mostly by Scenario B (PCW). The similarity index indicates a high degree of offer personalisation based on PCW referral, and as many as 61% of French e-commerce websites in our sample appear to be employing this type of personalisation. However, please note that these results are based on a small number of e-commerce websites (N<20) in each country and as such they should be treated with caution.

Table 36: Share of websites that personalise ranking of offers, by country

Country	Any scenario	Search engine (A1)	Price Comparison Website (B1)	Internet browser (C1)	Mobile device (D1)
Czech Republic	47%	33%	21%	33%	44%
France	70%	35%	61%	35%	45%
Germany	42%	28%	19%	17%	17%
Poland	79%	63%	56%	63%	68%
Romania	47%	41%	31%	35%	29%
Spain	58%	37%	35%	37%	32%
Sweden	75%	45%	60%	50%	50%
United Kingdom	65%	40%	42%	35%	45%

Note: A website is considered to be offer-personalising if its similarity index relative to the control shop is at least 10% smaller than the website's baseline index. For results using 10% and 20% threshold, please see the Annex. Sample size: 16-20 websites (varies by country and scenario)

Source: London Economics analysis of mystery shopping data

Offer personalisation compared to control steps

The control shops hide a substantial number of shopper characteristics from the e-commerce websites. Therefore, they do not allow us to isolate the impacts of different personalisation practices on offer personalisation. For example, if the similarity index between step A1 and the control shop is 0.80, we cannot tell to what extent this is driven by personalisation based on search engine and personalisation based on other observed characteristics (e.g. IP address or browsing history).

However, the mystery shopping exercise carries out control steps which only hide some shopper characteristics. Specifically, they block personalisation that is based on the individual shopper's past online behaviour (browsing history, search history, shopping history), while still allowing for personalisation based on technology used to access the e-

commerce website (PCW referral, search engine referral, direct URL access, browser used, device used, IP address etc.). Analysing differences between offers in personalised and control steps can therefore help to disentangle the effects of different types of personalisation. Specifically, offer differences between the personalised step and the control step should isolate personalisation based on the shopper's past online behaviour.

Generally, we would expect higher similarity indices between the personalised and control steps than we observed between the personalised and control shops, since the control steps screen off only some of the shopper's characteristics observable by the e-commerce retailer.

This is indeed the case. While similarity between personalised steps and control shops was estimated with index values of 0.76 to 0.80 (see Table 32), the similarity indices between personalised and control steps range from 0.87 to 0.94, showing considerably less offer variation. Similarly, while 61% of websites show different offers relative to the control shop (see Table 32), only 44% of websites use personalisation based only on the tracking of the shopper's behaviour.

The following table indicates that different personalisation practices have different impacts on offer personalisation. For example, panel A of Table 37 shows the impact of offer personalisation of the search engine. In step A1, mystery shoppers used their preferred search engine, while in step A2, they used DuckDuckGo, a search engine that doesn't track them. The mystery shopping found evidence that the change of search engine affects the product offer, but the similarity index between the two steps was very high, indicating that the effect of switching to DuckDuckGo is small (though significantly greater than noise at 95% confidence level). Correspondingly, the results suggest that only 16% of websites personalise based on information tracked by the search engine.

In step A3, shoppers accessed the e-commerce website through search in their preferred search engine, but using incognito browsing which screens off personalisation based on information about the shopper's online behaviour collected by the search engine, the browser or the e-commerce website itself. The similarity index between A3 and A1 is significantly lower than the baseline index at 99.9% confidence level, providing strong evidence of offer personalisation based on cookies or other information about the shopper's online behaviour. About a fifth of the e-commerce websites in the sample are found to personalise their offers based on this information. The fact that incognito browsing had greater effect on different product offers than using DuckDuckGo search engine suggests that personalisation based on tracked online behaviour relies more strongly on cookies and/or browsing history than on searching history as recorded by the search engine.

Table 37 : Offer personalisation by type of characteristics observable: comparing mystery shopping steps to control steps

Steps compared	Baseline index	Average similarity index	Share of websites that personalise offers	
Any control step (except B1vB2+)			44%	
Panel A: mystery shopping scenario A (Search engine)				
A1 v A2	0.95	0.94*	16%	
A1 v A3	0.95	0.92***	20%	
Panel B: mystery shopping scenario B (PCW)				
B1 v B2	0.95	0.87***	29%	
Panel C: mystery shopping scenario C (Browser)				
C1 v C2	0.95	0.93**	21%	
C1 v C3	0.95	0.92***	17%	

Steps compared	Baseline index	Average similarity index	Share of websites that personalise offers	
Any control step (except B1vB2+)			44%	
C2 v C4	0.95	0.90***	24%	
C3 v C4	0.95	0.94*	14%	
Panel D: mystery shopping scenario D (Mobile device)				
D1 v D2	0.94	0.94	10%	

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Source: London Economics analysis of mystery shopping data

In scenario B, the difference between the personalised and control step is expected to be largest. This is because, in B1, shoppers were referred to the e-commerce website through a Price Comparison Website (PCW), while in B2, they accessed the website directly and in incognito browsing. Therefore, B2 introduces an additional level of variation compared to the control steps in Scenario A. Step B2 varies both the route into the website and the ability of websites to track the shopper.

As expected, with a similarity index of 0.87, there is significantly more offer variation between the two steps than in the other scenarios, where the control step only introduced incognito browsing. Similarly, the share of websites identified as offer-personalising is 29% in this case, considerably more than for the other control steps. This provides further evidence that accessing an e-commerce website through a PCW seems to change the product offers that the e-commerce website displays to the shopper.

Scenario C explored personalisation based on the shopper's browser. This scenario enables us to isolate the impact of using one's preferred browser in 'regular' browsing mode (C1 vs C3); using 'incognito' mode in the preferred browser (C1 vs C2); and using 'incognito' mode in a browser not typically used (C2 vs C4). The control steps in Scenario C (C2, C4) differed from the personalised steps only in the use of incognito browsing.

The results suggest that a shopper's browser can affect the product selection shown to the shopper (comparing C1 vs C3). Interestingly, browser choice affects personalisation even in incognito mode (comparing C2 vs C4), indicating that a change of browser can affect offers even if incognito browsing is used and the tracking of online behaviour therefore disabled. About a fifth of the websites in the sample personalise their offers based on the consumer's browser.

The results also suggest that there is personalisation based on the ability to track browsing history, even when the shopper switches to a different browser than they typically use (C1 vs C2 and C3 vs C4). Again, we observe significant variation between the personalised steps (C1, C3) and their respective control steps (C2, C4).

At almost 0.94, the index comparing the personalised and control steps in Scenario D (mobile device) was not significantly lower than the baseline index. This suggests that there is evidence of offer personalisation based on mobile devices (see Table 32), but the personalisation cannot be entirely explained by cookies and the seller's ability to track the shopper's browsing history.

Offer personalisation compared to control steps, by products and countries

When we further break down offer personalisation compared to the control steps, we see that the results are to some extent driven by the hotels sector. This suggests, from the evidence collected in the mystery shopping, that e-commerce websites offering hotel

⁺ B1vB2 is excluded because it is not consistent with the other control steps. B2 varies both the route into the website as well as the ability of websites to track the shopper, while other control steps vary only the latter.

rooms are particularly likely to personalise offers based on information collected about the shopper through cookies or other forms of tracking online behaviour.

Airline tickets also display relatively low similarity indices, but since the sector displays more random variation, most results are not significantly different from the baseline index i.e. we cannot reject the hypothesis that offer variation is because of random noise.

The notable exception is mystery shopping scenario B, which looked at the effects of PCWs. Unlike the control steps in other scenarios, the control step in B2 did not only hide information about the shopper's past online behaviour, but also altered the way the shopper accessed the e-commerce website. In B1, it was through a PCW, while in B2, the shopper accessed the website directly. As a result, the observed offer differences between B1 and B2 are much higher than in the other scenarios, confirming earlier evidence (see Table 32) that access through a PCW has significant effect on the product offer.

Table 38 : Offer personalisation compared to control step, by product

Product	Baseline desktop/ laptop	A1 v A3	B1 v B2	C1 v C2	Baseline mobile device	D1 v D2
Airline ticket	.84	.86	.78***	.92	.83	.89
Hotel	.94	.85***	.74***	.82***	.93	.90*
Sport shoes	.98	.99	.96**	1.00	.98	.98
TV	.98	.98	.96*	.97*	.97	.99

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample size: 99-169 shops (varies by product category and scenario)

Source: London Economics analysis of mystery shopping data

Looking at the shares of websites that are identified as offer-personalising, the same pattern emerges. This indicates that the results are not driven by large offer differences on a small number of websites. In the hotel sector, 76% of e-commerce websites in our sample personalise offers based on cookies or other tracked behaviour.

Table 39: Share of websites that personalise offers based on tracking users, by product

Product	Any control step (except B1vB2 ⁺)	A1 v A3	B1 v B2	C1 v C2	D1 v D2
Airline ticket	66%	37%	51%	26%	13%
Hotel	76%	30%	45%	46%	27%
Sport shoes	13%	5%	17%	5%	0%
TV	26%	8%	5%	8%	3%

Note: A website is considered to be offer-personalising if its similarity index relative to the control step is at least 10% smaller than the website's baseline index. For results using 5% and 20% threshold, please see the Annex. + B1vB2 is excluded because it is not consistent with the other control steps. B2 varies both the route into the website as well as the ability of websites to track the shopper, while other control steps vary only the latter. Sample size: 33-39 websites (varies by country and scenario)

Source: London Economics analysis of mystery shopping data

Disaggregating by Member States, only the data collected in the UK and Poland provide sufficient evidence to confidently reject the hypothesis of no offer personalisation in most scenarios. In addition, offer personalisation is found between steps B1 and B2 in all countries except Germany, the Czech Republic and Romania; and between steps A1 and A3 in Romania (see Table 40).

Table 40: Offer personalisation compared to control step, by country

Country	Baseline desktop/l aptop	A1 v A3	B1 v B2	C1 v C2	Baseline mobile device	D1 v D2
Czech Republic	.93	.97	.96	.98	.98	.99
France	.92	.90	.83*	.88	.93	.91
Germany	.97	.96	.93	.99	.92	.97
Poland	.94	.85**	.81*	.86**	.90	.91
Romania	.99	.90***	.98	.98	.98	.97
Spain	.98	.96	.89**	.97	.97	.96
Sweden	.93	.92	.85**	.92	.92	.92
United Kingdom	.98	.91**	.74***	.86***	.95	.92

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample size: 44-84 shops (varies by country and scenario)

Source: London Economics analysis of mystery shopping data

We note, however, that failure to reject the hypothesis of no offer personalisation cannot be interpreted as strong evidence of no personalisation. At the disaggregated levels, the findings are based on a smaller sample size, which reduces the power of the statistical test – that is, the test's ability to reject the null hypothesis if the null is false. This means that it becomes more probable that the test does not reject the hypothesis of no offer personalisation even if the offer was, in fact, personalised.

Looking at the e-commerce websites by country, we again observe that only in Poland and the UK a considerable number of websites are identified as offer-personalising in individual control steps.

However, the results change if we consider the share of websites that display different offers in *any* of the steps compared to the control step i.e. if websites display different offers in the mystery shopping step A1 compared to control step A2, or mystery shopping step A1 compared to A3, or mystery shopping step C1 compared to control step C2, or mystery shopping step C3 versus control step C4, or mystery shopping step D1 versus control step D2. In this case, France, Spain and Sweden have a substantial share of offer-personalising websites, with 45%, 47% and 65% of websites respectively.

This suggests that different websites track their users in different ways. As a consequence, a small share of websites may employ any one particular technique (e.g. personalisation based on search history), but a relatively large share employ *some* kind of offer personalisation based on the consumer's previous online behaviour.

Table 41: Share of websites that personalise offers based on tracking users, by country

Country	Any control step (except B1vB2 ⁺)	A1 v A3	B1 v B2	C1 v C2	D1 v D2
Czech Republic	21%	5%	16%	11%	0%
France	45%	15%	44%	30%	10%
Germany	26%	16%	12%	5%	5%
Poland	53%	37%	31%	32%	5%
Romania	29%	24%	13%	12%	12%
Spain	47%	16%	29%	16%	5%
Sweden	65%	15%	35%	25%	20%
United Kingdom	65%	32%	47%	35%	25%

Note: A website is considered to be offer-personalising if its similarity index relative to the control shop is at least 10% smaller than the website's baseline index. For results using 10% and 20% threshold, please see the Annex. Sample size: 16-20 websites (varies by country and scenario)

Source: London Economics analysis of mystery shopping data

Personalisation scenarios compared to each other based on access route

While the control steps were designed to isolate effects of personalisation based on the shopper's tracked online behaviour, the scenarios varied the access route of the shopper to the e-commerce website. Comparing either the personalised steps *between* scenarios (e.g. A1 against B1) or the control steps between scenarios (e.g. A3 against D2) can isolate the effect of the referral route or technology accessed. For example, comparing offers in A3 and C2 should reveal differences between personalisation based on search engine referral and direct access to the website through URL.

Table 42 shows differences in similarity index for each comparison. All differences are statistically significantly greater than the baseline index, suggesting that the differences cannot be explained by random variation. PCW scenario (B1) displays largest offer differences compared to any of the other scenarios.

The mystery shopping data therefore suggests that regardless of the browsing mode (regular or incognito), the access route to a website is an important source of offer personalisation. These differences are significantly larger than the differences between the personalised steps and their respective control steps. This suggests that based on the data in our sample, the technology used to access an e-commerce website is a more important driver of offer personalisation than information about the individual consumer's past online behaviour.

⁴⁰⁰ Control step B2 cannot be used because it both blocked tracking and varied access route to website compared to step B1

Table 42: Offer personalisation by type of characteristics observable: comparing mystery shopping steps to each other

Steps compared	Baseline index	Average similarity index	Share of websites that personalise offers
Any of the pairs below			54%
Regular browsing			
A1 v B1	0.95	0.70***	44%
A1 v C1	0.95	0.88***	28%
A1 v D1	0.95	0.83***	35%
B1 v C1	0.95	0.70***	42%
B1 v D1	0.95	0.68***	46%
C1 v D1	0.95	0.87***	25%
Incognito browsing			
A3 v C2	0.95	0.86***	31%
A3 v D2	0.95	0.84***	32%
C2 v D2	0.95	0.84***	36%

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample size: 461-643 shops (varies by steps compared)

Source: London Economics analysis of mystery shopping data

Disaggregating the results by product category again reveals most offer personalisation in the services sectors – airline tickets and hotels. The access route to the e-commerce website through a PCW stands out in particular. In the case of the airline tickets sector, the similarity indices relative to the other scenarios are as low as 0.39 (compared to mobile device access), 0.40 (compared to search engine access) and 0.45 (compared to direct URL access). In the case of hotels, the values are comparable. By contrast, in the case of sport shoes and TVs, the similarity indices are almost uniformly above 0.90, sometimes not even significantly different from random noise.

Table 43: Offer personalisation by referral route to e-commerce website and product category

Product	Baseline	A1 v B1	A1 v C1	A1 v D1	B1 v C1	B1 v D1	C1 v D1
Airline ticket	.84	0.40***	0.78***	0.72***	0.45***	0.39***	0.80***
Hotel	.94	0.37***	0.84***	0.74***	0.37***	0.33***	0.78***
Sport shoes	.98	0.97*	0.98	0.95**	0.97	0.94**	0.97
TV	.98	0.94**	0.92***	0.90***	0.90***	0.89***	0.90***

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample size: 111-168 shops (varies by country and scenario)

Source: London Economics analysis of mystery shopping data

Disaggregating by country shows that access route to the website leads to offer differences that cannot be explained by random variation in all countries in our sample. In particular, access through PCW is associated with significant differences in all countries and compared to any other referral route. By contrast, when comparing search engine (Scenario A) with

direct URL access (Scenario C), significant offer differences are recorded only in Germany, Poland, Romania and the UK. Table 44 shows the complete results.

Table 44: Offer personalisation by referral route to e-commerce website and country

Country	Baseline	A1 v B1	A1 v C1	A1 v D1	B1 v C1	B1 v D1	C1 v D1
Czech Republic	.93	0.72***	0.93	0.93	0.73***	0.73***	0.97
France	.92	0.57***	0.90	0.86*	0.59***	0.57***	0.90
German y	.97	0.89**	0.89**	0.85***	0.83**	0.82***	0.90*
Poland	.94	0.49***	0.77***	0.75***	0.49***	0.50***	0.77***
Romania	.99	0.73***	0.82***	0.81***	0.78***	0.77***	0.96**
Spain	.98	0.74***	0.95	0.93*	0.75***	0.76***	0.96
Sweden	.93	0.74***	0.89	0.81***	0.70***	0.67***	0.78***
United Kingdom	.98	0.68***	0.87***	0.74***	0.67***	0.55***	0.74***

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample size: 44-86 shops (varies by country and scenario)

Source: London Economics analysis of mystery shopping data

The mystery shopping data suggest that most of the offer variation that cannot be attributed to random noise is due to the technology/referral route used to access the website. Tracking online behaviour of individual consumers seems to explain a smaller share of observed offer variation. In particular, access through a PCW seems to lead to largest offer differences compared to the other scenarios.

Offer personalisation by size of e-commerce website

Using traffic data obtained from SimilarWeb as a proxy for the size of an e-commerce website, it is possible to estimate whether smaller or larger websites are more likely to personalise offers. Websites are considered "smaller"/"larger" if their traffic is less/more than the median traffic in our sample.

The results suggest that on average, smaller websites personalise offers more than larger websites. A closer inspection shows that "smaller" websites in our sample seem to personalise offers more primarily because size is related to product category. According to the data of the 160 websites analysed, e-commerce websites selling services (hotels, airline tickets) are more likely to be "smaller" by traffic volume, while websites selling goods (TVs, sport shoes) are more likely to be "large". As the chapter showed earlier, the services sector exhibits more offer personalisation than the goods sector.

Dividing the websites between "large" and "small" by splitting them along the median traffic within each product category controls for this composition effect. When the effect is controlled for, size no longer explains the extent of offer personalisation. Table 45 shows that this holds for all types of personalisation scenarios considered. The difference is not statistically significant in any step (offer similarity is measured compared to the control shop). Therefore, the mystery shopping exercise did not find evidence that size of the e-commerce website influences the extent of offer personalisation.

Given that e-commerce websites in more populous countries have naturally larger number of visitors, it could be argued that using traffic volumes captures the differences between large countries and small countries rather than between large websites and small websites. As a robustness check, therefore, we approximate a website's size not by its volume of monthly visitors, but rather by its national rank in terms of monthly visits, also provided

by SimilarWeb. As a second check, we weigh the traffic data by the country's population. In both cases, the results are unchanged.

Table 45: Differences in similarity index between smaller and larger websites, by type of personalisation

Scenario	Steps compared with the control shop	Similarity index of smaller websites	Similarity index of larger websites	Difference
	A1	0.79	0.81	-0.02
Search engine	A2	0.79	0.78	0.01
	A3	0.80	0.81	-0.01
PCW	B1	0.77	0.80	-0.03
	B2	0.79	0.79	0.00
	C1	0.78	0.81	-0.03
Browser	C2	0.77	0.76	0.01
2101100	C3	0.78	0.80	-0.02
	C4	0.77	0.80	-0.03
Mobile device	D1	0.76	0.78	-0.02
	D2	0.75	0.78	-0.03

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. Two-sided mean comparison t-test was used.

Sample size: 160 websites

Source: London Economics analysis of mystery shopping data

5.1.2. Evidence of personalised pricing

The economic valuation exercise assessed whether shoppers face significantly different prices depending on:

- Whether sellers can observe their personal characteristics, or not; or
- The type of personal information that sellers can observe.

In order to make this comparison, the incidence of price personalisation is examined using the following procedure (further details are provided in the Annex):

- For any pair of situations, identical products are matched. The exercise identifies the set of unique products shown to both mystery shoppers in e.g. scenario A and in the control step, OR in scenario D and the control shop; and
- Percentage price differences between matched products are recorded in absolute values
- The average price difference is computed between the two situations.

Note that this method merely aims to detect the occurrence and extent of personalised pricing, i.e. the method computes average absolute price differences ignoring the sign of

the price differences. Section 5.1.3 takes into account also the direction of price variations to estimate the *net* effect on consumers.

In addition, the analysis needs to account for random variation in e-commerce results, leading to price differences between even identical steps. To address this issue, the study constructs a baseline index to account for random variation, similar to the procedure conducted for the baseline difference in offers (see Section 5.1.1 and the Annex for more detail on construction of the baseline price difference).

There is one key difference between the methodological approaches to analysing offer personalisation compared to price personalisation – namely the unit of observation. When analysing offer personalisation, the unit of observation was an 'offer': the top 5 ranking products shown to a shopper in the control shop, or in one of the mystery shopping steps. It was necessary for the 'top 5 offer ranking' to be the unit of observation since the analysis needed to construct a similarity index based on the offers shown to a shopper in a situation (a personalisation step or the control shop). Therefore, the offer personalisation could not perform analysis at product level, leading to smaller sample sizes.

By contrast, the unit of observation in the price personalisation analysis was the individual product. This is because the analysis considers the price of a specific product in one situation and compares it to the price of the same product in a different situation, regardless of the rank order in which the product appeared in either situation. For example, the analysis compared the price of a product in mystery shopping scenario D, compared the control shop.

One advantage of changing the unit of analysis is an increased sample size. While the analysis of personalised offers relied on approximately 700 shops that each recorded a top 5 ranking of products, the number of individual product matches anywhere in the ranking is far higher.

A second advantage is that unlike the similarity index for offer personalisation, price differences can be readily aggregated. It is possible therefore to compare individual steps (see Table 32) to the control shop or to each other. It is also possible to present aggregate (and average) price differences relative to the control shop recorded in multiple steps. We can therefore present results also by entire scenario (taking into account product matches in all of the steps within the scenario) or aggregate even across scenarios for an overall measure of average price personalisation.

The following sections describe price personalisation results comparing personalisation scenarios to:

- The control shop (where sellers can observe no, or extremely limited, personal information); and
- Control steps (where sellers can observe some personal information, but cannot track the shoppers' online behaviour).
- Each other

Throughout, results are presented in aggregate as well as at the level of individual product category, Member State and personalisation step/scenario.

Personalisation scenarios compared to control shops

This section considers all personalisation scenarios together, discussing whether shoppers face different prices overall when sellers can observe their personal characteristics, compared to when sellers cannot.

We first present average absolute price differences between two situations: any scenario where e-commerce websites can observe shoppers' personal characteristics, compared to the control shop where websites cannot observe any personal characteristics.

Consumer market study on online market segmentation through personalised pricing/offers in the European Union

The mystery shopping exercise suggests that there are statistically significant, but small, differences between the control shops and personalised scenarios overall. When websites can observe shoppers' personal characteristics, average prices differ by 0.22% from the price of the same product when consumers' characteristics are hidden. Note that this difference could both be positive or negative. While small, the difference is statistically significantly higher than random price variation at 99.9% level.

Disaggregating this result by product category shows that the variation is driven mostly by the airline ticket and hotel sectors, with respective average price variation of 0.67% and 0.30%. Both are statistically significantly higher than their baseline variation of 0.13% and 0.16%.

The estimates for price personalisation in the airline ticket sector are significant in all countries except Sweden, with the highest average variation (1.78%) observed in Spain. In the hotel sector, absolute price personalisation is significantly different from random noise in all countries except Sweden and the Czech Republic.

By contrast, personalisation affects average prices of sport shoes and TVs only by 0.08% and 0.02%, respectively. Nevertheless, in the case of TVs, this is still significantly more than the random variation of 0.01%.

In the case of sports shoes, average prices are not significantly different from random variation, except in Germany (0.20%), Poland, Spain, and the UK (all 0.06%). The highest variation for TV prices was observed in Spain (0.10%) and Sweden (0.04%).

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⁴⁰¹ Details of how average prices are computed are discussed in the Annex A1.10.

Table 46: Incidence of price personalisation, by country, product, and total

Country/Product	All products		Airline ticket	irline ticket		Hotel		Sport shoes		TV	
	Baseline variation	Price difference	Baseline variation	Price difference	Baseline variatio n	Price difference	Baseline variation	Price differenc e	Baseline variation	Price differenc e	
All countries	0.10%	0.22%***	0.13%	0.67%***	0.16%	0.30%***	0.12%	0.08%	0.01%	0.02%***	
Czech Republic	0.00%	0.20%***	0.00%	0.58%***	0.00%	0.36%	0.00%	0.04%	0.00%	0.01%**	
France	0.29%	0.21%	0.11%	0.59%***	0.07%	0.14%***	0.94%	0.22%	0.00%	0.01%	
Germany	0.05%	0.16%***	0.39%	0.76%***	0.00%	0.04%**	0.00%	0.20%***	0.02%	0.02%	
Poland	0.05%	0.24%***	0.00%	0.12%***	0.19%	0.93%***	0.00%	0.06%***	0.00%	0.01%*	
Romania	0.11%	0.18%***	0.00%	1.06%***	0.53%	0.23%***	0.00%	0.00%***	0.00%	0.00%*	
Spain	0.09%	0.43%***	0.18%	1.78%***	0.15%	0.32%***	0.00%	0.06%**	0.04%	0.10%***	
Sweden	0.23%	0.24%	0.40%	0.55%	0.51%	0.51%	0.01%	0.00%	0.00%	0.04%**	
United Kingdom	0.01%	0.12%***	0.02%	0.31%***	0.00%	0.12%***	0.00%	0.06%**	0.00%	0.00%*	

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used. Sample sizes: All products and all countries: 34,403 product matches.

By product: 6,031-10,184 product matches (varies by product)

By country: 3,506-5,014 product matches (varies by country)

By country and product: 472-1,502 product matches (varies by product and country)

Source: London Economics analysis of mystery shopping data

While statistically significant, even the largest results are noticeably small. This is primarily because in 94% of the 34,403 matched product pairs, there was no price difference at all. However, even among the remaining 6% product pairs where some price difference was recorded, the median difference is less than 1.6%. The following histogram shows the frequency distribution of products with non-zero price differences relative to the control shop.

900 100.0% 99.5% 800 99.0% 700 98.5% 600 98.0% 97.5% Frequency 500 97.0% 400 96.5% 300 96.0% 95.5% 200 95.0% 100 94.5% 0 94.0% 3.5% 10.5% 2% 5% 12. 13. 14. 15. 16. Absolute value of price difference relative to control shop

Figure 63: Distribution of products with non-zero price difference relative to the control shop

Sample size: 2061 product matches with non-zero price difference representing 6% of all product matches **Source: London Economics' analysis of mystery shopping data**

Number of product matches

The use of price personalisation by e-commerce websites therefore seems to be very limited, though still statistically distinguishable from random noise.

Cumulative frequency

The rest of this section further disaggregates these results by personalisation steps and scenarios to examine whether the detected instances of price personalisation result from specific types of personalisation techniques.

Personalisation scenarios compared to control shops, by type of personalisation

At the most detailed level of personalisation set-up, we can look at each step of each scenario. The scenarios varied the access route to the e-commerce website (e.g. search engine, PCW...), while the steps within each scenario varied the e-commerce site's ability to observe the shopper's past online behaviour (see Table 31). Table 47 shows average price personalisation for each step. The largest average price difference compared to the control products (0.77%) was observed in step B1, in which the mystery shopper accessed the e-commerce website through a PCW. Section 5.1.5 looks more closely at personalisation based on a referral from a PCW.

Table 47: Price personalisation, by type of shopper characteristic observable – comparison with the control shop

Steps compared	Baseline price variation	Percentage price difference
A1	0.10%	0.17%**
A2	0.10%	0.18%**
A3	0.10%	0.22%***
B1	0.10%	0.77%***
B2	0.10%	0.44%***
C1	0.10%	0.16%*
C2	0.10%	0.17%*
C3	0.10%	0.14%
C4	0.10%	0.14%
D1	0.04%	0.17%***
D2	0.04%	0.15%***

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample sizes: 2003-2844 (varies by step)

Source: London Economics' analysis of mystery shopping data

In nearly all steps, the recorded price differences are small but statistically significantly larger than random variation, with levels varying from 0.15% (D2) to 0.77% (B1). The two exceptions were steps C3 and C4, in which the shopper used a browser they don't usually use in regular and private browsing, respectively. The recorded price differences were not significantly larger than the baseline.

Breaking these results down by sector, we see a consistent pattern of larger price personalisation in services (hotel rooms and airline tickets) and smaller in goods (sport shoes and TVs).

The results also indicate that PCW referral seems to lead to the largest absolute price differences in the airline sector (3.41%). The impact of browser, on the other hand, seems to be the smallest in all sectors except sport shoes (but the result for sport shoes is still not statistically distinguishable from random noise).

Table 48: Price personalisation compared to control shop, by product category

Product	Baseline desktop/ laptop	Search engine (A)	Price Comparison Website (B1)	Internet browser (C)	Baseline mobile	Mobile device (D)
Airline ticket	0.13%	0.55%***	3.41%***	0.37%***	0.14%	0.35%***
Hotel	0.16%	0.28%***	0.65%	0.21%*	0.00%	0.30%***
Sport shoes	0.12%	0.07%	0.14%	0.10%	0.02%	0.07%**
TV	0.01%	0.02%***	0.08%**	0.02%**	0.04%	0.02%*

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample sizes: 330-649 in scenario B, 1847-3205 in others (varies by scenario and product category)

Source: London Economics' analysis of mystery shopping data

At country level, again, we see that the aggregate results are to a significant extent driven by the PCW scenario. In the Czech Republic, for example, there is 1.59% price variation in the PCW scenario and less than 0.04% in the other scenarios.

Table 49: Price personalisation compared to control shop, by country

Country	Baseline desktop/ laptop	Search engine (A)	Price Compariso n Website (B1)	Internet browser (C)	Baseline mobile	Mobile device (D)
Czech Republic	0.00%	0.01%**	1.59%**	0.02%	0.00%	0.04%
France	0.29%	0.07%	1.25%***	0.11%	0.05%	0.32%***
Germany	0.05%	0.20%***	0.39%***	0.08%***	0.08%	0.09%**
Poland	0.05%	0.31%***	0.20%*	0.19%***	0.00%	0.21%***
Romania	0.11%	0.11%***	0.89%***	0.10%***	0.00%	0.05%**
Spain	0.09%	0.53%***	0.46%**	0.44%***	0.02%	0.29%***
Sweden	0.23%	0.25%	0.71%**	0.18%	0.18%	0.15%
United Kingdom	0.01%	0.10%***	0.36%***	0.10%***	0.01%	0.13%***

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample sizes: 168-338 in Scenario B, 773-1601 in others (varies by scenario and country)

Source: London Economics' analysis of mystery shopping data

Personalisation scenarios compared to control steps

The control shop screens a substantial number of personal characteristics from the seller. The control steps (A2, A3, B2, C2, C4, D2), on the other hand, only screen personalisation

based on the website's ability to track the shopper's online behaviour (e.g. through cookies). Comparing the prices in personalisation scenarios with the control steps should therefore allow us to isolate the impact of tracking techniques on prices.

In most cases, the website's ability to track consumers does not seem to lead to price personalisation. For example, in step A1 the shopper accessed the e-commerce website through his/her preferred search engine. In step A2, the shopper used DuckDuckGo, a search engine that doesn't track its users. The change led to limited price difference that could be explained by random variation. Similarly, in step A3, the shopper used incognito browsing, which prevents the website from using cookies or other information about the shopper's previous behaviour to tailor prices. Again, this led to price differences that were not statistically significantly larger than noise. The same applies to all control steps in scenarios C (browser) and D (mobile device).

The only control step that led to statistically significant price variation was in scenario B. However, we note that these results may be driven by the different set-up of the mystery shopping exercise in this scenario. In B1, shoppers were referred to the e-commerce website through a Price Comparison Website (PCW), while in B2, they accessed the website directly and in incognito browsing. Therefore, B2 introduces an additional level of variation compared to the control steps in Scenarios A, C, and D. Step B2 varies both the route into the website and the ability of websites to track the shopper. It does not therefore isolate the impact of the website's ability to track the shopper.

Table 50: Price personalisation compared to control steps

Steps compared	Baseline price variation	Average price difference
Panel A: mystery sh	opping scenario	A (Search engine)
A1 v A2	0.10%	0.09%
A1 v A3	0.10%	0.14%
Panel B: mystery sh	opping scenario	B (PCW)
B1 v B2	0.10%	0.34%***
Panel C: mystery sh	opping scenario	C (Browser)
C1 v C2	0.10%	0.08%
C1 v C3	0.10%	0.10%
C2 v C4	0.10%	0.12%
C3 v C4	0.10%	0.07%
Panel D: mystery sh	opping scenario	D (Mobile device)
D1 v D2	0.04%	0.08%

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample sizes: 2164-3076 (varies by scenario)

Source: London Economics' analysis of mystery shopping data

The mystery shopping data therefore do not provide evidence that e-commerce websites' ability to track the online behaviour of shoppers leads to price personalisation. The lack of results, however, should not be interpreted as evidence to support the hypothesis that websites do not engage in such practices.

Comparing the prices recorded by mystery shoppers to the control shops revealed price variation that could not be completely explained by random noise. However, it is more difficult to isolate the impact on prices of one particular type of observable characteristics.

It is possible that each channel through which websites can personalise prices can be individually not statistically significant, even if the combined effect of all channels is statistically significant.

Consider this hypothetical example. Suppose that the website's ability to observe the shopper's access route to the website leads to the average price difference of 0.15%. Further assume that the website's ability to observe the users' cookies also leads to 0.15% price variation. However, in a situation where the website can observe both the access route and cookies, the observed variation is 0.26%. A statistical test would compare the observed price differences to an estimated random price variation of (say) 0.10% (random price difference occurring for example due to A/B testing). It is possible that the statistical test will be unable to find evidence of personalisation either in the case of access route or cookies, but it would reject the hypothesis of no personalisation based on their combined effect.

Personalisation scenarios compared to each other

While the control steps were designed to isolate effects of personalisation based on the shopper's tracked online behaviour, the scenarios varied the access route of the shopper to the e-commerce website. Comparing either the personalised steps *between* scenarios (e.g. A1 against B1) or the control steps between scenarios (e.g. A3 against D2) can isolate the effect of the referral route or technology accessed.⁴⁰² For example, comparing prices in A3 and C2 should reveal differences between personalisation based on search engine referral and direct access to the website through URL.

Table 51 shows price differences for each comparison. PCW scenario (B1) again displays largest price differences compared to any of the other scenarios, confirming earlier evidence that PCW referral is associated with the strongest evidence of price personalisation. A further statistically significant result is between A1 and D1 and between A3 and D2.

This suggests that regardless of the browsing mode (regular or incognito), access through search engine on a desktop is associated with prices different from when accessing a website directly but via a mobile device. The effect is very small, but beyond the levels that could be explained by random variation alone. The same is observed between scenarios C (browser, desktop) and D (preferred browser on mobile device), but not between A (search engine, desktop) and C (directly via browser, desktop), suggesting it is the mobile technology driving the difference.

⁴⁰² Control step B2 cannot be used because it both blocked tracking and varied access route to website compared to step B1

Table 51: Price personalisation compared between steps with different types of personalisation

Steps compared	Baseline price variation	Percentage price difference					
Browsing with enabled tracking							
A1 v B1	0.10%	0.77%***					
A1 v C1	0.10%	0.13%					
A1 v D1	0.10%	0.15%*					
B1 v C1	0.10%	0.74%***					
B1 v D1	0.10%	0.77%***					
C1 v D1	0.10%	0.17%*					
Incognito brows	ing						
A3 v C2	0.10%	0.12%					
A3 v D2	0.10%	0.19%**					
C2 v D2	0.10%	0.15%*					

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample sizes: 1657-2954 product matches (varies by step pair)

Source: London Economics' analysis of mystery shopping data

Disaggregating the statistically significant results by product category, we observe that the variation of other steps relative to Scenario B (PCW) is mostly driven by the airline sector. This confirms the evidence presented in Table 48 which showed notable price differences in the airline sector in Scenario B (PCW) as compared to the control shop.

However, Table 52 also shows that the differences between scenarios A (search engine) and C (browser) compared to scenario D (mobile phone) are also mostly driven by the airline sector. These results were not observed earlier in Table 48 which did not suggest notable differences in the airline sector between the mobile scenario and the laptop/desktop scenarios. Section 5.1.3 examines the signs of the price differences (i.e. whether personalised prices are higher or lower than in the control shop) to shed more light on the issue.

Table 52: Price personalisation compared between steps with different types of personalisation, by product category

Product	Baseline	A1 v B1	A1 v D1	B1 v C1	B1 v D1	C1 v D1
Airline ticket	0.13%	4.77%***	0.41%***	4.36%***	4.83%***	0.49%***
Hotel	0.16%	0.51%*	0.23%	0.63%	0.48%	0.18%
Sport shoes	0.12%	0.05%	0.04%	0.08%	0.05%	0.09%
TV	0.01%	0.11%***	0.03%**	0.08%**	0.08%**	0.00%*

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample sizes: 237-819 in (varies by scenario and product category)

Source: London Economics' analysis of mystery shopping data

Comparing personalisation scenarios to each other enables us to isolate the effect of technology used to access the website. This comparison confirms evidence presented earlier that PCW referral is associated with largest price differences that consistently cannot be explained by random variation. It also suggests that use of mobile device can lead to different prices compared to the use of desktop/laptop. The effect appears in both cases to be driven primarily by the airline ticket sector.

Share of websites that personalise prices

The above analysis assessed whether shoppers on e-commerce websites see different prices when their personal characteristics are observable compared to when they are not. The effect seems however very limited in magnitude and prevalence, with more than 94% of all observed product matches exhibiting no price differences at all and the remaining 6% a median of 1.6% price difference.

This section looks at website-level data to identify the share of websites in our sample that personalise prices based on observable characteristics.

With 20-384 product matches per website, it is possible for us to conduct statistical tests for the majority of the websites⁴⁰³, comparing each website's average price difference to the baseline variation of its sector.

The mystery shopping data suggests that across all types of personalisation:

- When shoppers' personal characteristics are observable, 34 websites (out of 153) show prices with more variation compared to the control shop than can be explained by random noise
- Of the 34, 19 belong to the airline ticket sector, 9 to the hotel sector, 4 to the shoes sector and 2 to the TV sector

⁴⁰³ Three websites with fewer than 50 product matches are excluded. Fewer than 50 products would not guarantee sample size large enough to perform statistical tests on. In addition, 4 websites were excluded because in all shops on each website, the prices were reported in inconsistent currencies (or there were data problems). For more details on excluded observations, see our methodological choices in the Annex. Websites, where the statistical test indicated significant price difference, but the average difference was lower than 0.1%, are excluded from this count. This is because price changes of this magnitude are unlikely to be due to personalisation. They can reflect, for example, the fact that some mystery shoppers rounded prices to the nearest euro (or other currency unit), while the control shopper did not (or vice versa). If these websites are also included, the total number of websites where statistically significant price difference was observed would be 48.

• The average difference exceeds 1% on 16 websites, with the largest average just under 4%. All of the 16 belong either to the airline ticket or hotel sectors

Price personalisation by website size

As before, using traffic data obtained from SimilarWeb as a proxy for the size of an e-commerce website, we could estimate whether smaller or larger websites are more likely to personalise prices. Websites are considered "smaller"/"larger" if their traffic is less/more than the median traffic in our sample.

The results suggest that on average, smaller websites personalise more than larger websites. In the case of offer personalisation, this finding was largely attributable to the fact that the websites in sectors with most personalisation (airline tickets, hotels) tended to be among the smaller websites. When websites were split into smaller/larger by comparing them only with websites in the same product category, the effect of size on offer personalisation disappeared.

In the case of price personalisation, the effect remains significant. Across all types of personalisation, product categories, and countries, the average price difference for "small"⁴⁰⁴ websites is 0.28%, while for the "larger" websites 0.15%. The difference is statistically significant at 99.9% confidence level. Disaggregating by product category finds that the result is driven mostly by the airline and hotel sectors, where there is also evidence of dynamic pricing.

Given that e-commerce websites in more populous countries have naturally larger number of visitors, it could be argued that using traffic volumes captures the differences between large countries and small countries rather than between large websites and small websites. As a robustness check, therefore, we approximate a website's size not by its volume of monthly visitors, but rather by its national rank in terms of monthly visits, also provided by SimilarWeb. As a second check, we weigh the traffic data by the country's population. In both cases, the results are broadly unchanged, though the estimated effect is smaller. Absolute website size seems to influence the extent of price personalisation more strongly than website size relative to the size of the market.

One reason for this may be that larger websites may be more likely to be scrutinised for evidence of price personalisation, and therefore larger websites may have a disincentive to personalise prices. Another reason may be that smaller websites in our sample are more sensitive to small traffic increases compared to larger websites, and therefore are observed to personalise more often. This is consistent with the observation that the effect is driven by the services sectors, where dynamic pricing is more prevalent.

5.1.3. Net effect of price personalisation

The analysis of mystery shopping data found evidence that consumers face different prices when their personal characteristics are observable compared to when they are not (see section 5.1.2). The differences were more common in the services sectors (airline tickets, hotels) than in the goods sectors (sport shoes, TVs). While the research found price differences statistically significantly different from random noise, differences were on average small in magnitude. This is because for an overwhelming majority of products no difference was recorded, and because even the recorded differences were usually small.

So far, the analysis ignored the sign of the price differences, merely observing their absolute deviation from control prices. However, to assess the impact of price personalisation on consumers, the direction of the price differences needs to be taken into account. This section looks at whether shoppers on average face higher or lower prices

⁴⁰⁴ "Small" or "large" here means not relative to the whole sample, but relative to websites in the same product category.

when their personal characteristics are observable. The results are also disaggregated by type of personalisation, product, and country.

In order to make this comparison, the net effect of price personalisation is examined using the following procedure (further details are provided in the Annex):

- For any pair of situations, identical products are matched. The exercise identifies the set of unique products shown to both mystery shoppers in e.g. scenario A and in the control step, OR in scenario D and the control shop; and
- Percentage price differences between matched products and their sign are recorded
- The average net price difference is computed between the two situations.

In addition, the analysis needs again to account for random variation in e-commerce results, leading to price differences between even identical steps. In particular, there may be a bias if random variation consistently increases or decreases product prices. Therefore, the net effect of price personalisation must be determined accounting for this bias rather than relative to no price difference. To address this issue, the study constructs a baseline index to account for random variation, similar to the procedure conducted for the baseline difference in offers (see Section 5.1.1 and the Annex for more detail on the construction of the baseline price difference).⁴⁰⁵

The following sections describe net price personalisation results comparing personalisation scenarios to:

- The control shop (where sellers can observe no, or extremely limited, personal information); and
- Control steps (where sellers can observe some personal information, but cannot track the shoppers' online behaviour).
- Each other

Throughout, results are presented also at the level of individual product category, Member State and type of personalisation.

Personalisation scenarios compared to control shops

This section discusses whether shoppers face higher or lower prices overall when sellers can observe their personal characteristics, compared to when sellers cannot.

The mystery shopping exercise suggests that overall, taking into account all types of personalisation, products, and countries, there is no statistically significant price difference in either direction between the control shops and personalised scenarios. At the level of product category, the data shows that sport shoes are cheaper and TVs more expensive when shopper characteristics are observable, but the effect is in both cases very limited in magnitude. 406

No consistent patterns emerge even when the results are further disaggregated by Member State. While in some countries airline tickets are slightly cheaper (<1%) when shopper characteristics are observable (UK, Sweden, Czech Republic) compared to the control shop, in others they are modestly more expensive (Germany, Romania), and in yet others there is no significant difference (Spain, Poland, France). Similarly, the price of hotels is 0.44% lower in Poland when personalisation is not possible, but 0.23% higher in Spain. In the category of sport shoes and TVs, the same variation can be observed, but at even lower magnitudes.

⁴⁰⁵ The baseline however is not statistically significant in most cases, so the tests check if the observed price difference is significantly different from 0 (rather than from the baseline).

 $^{^{406}}$ Details of how average prices are computed are discussed in the Annex A1.10.

Table 53: Overall price personalisation, by country, product, and total

Country/Product	All products	Airline ticket	Hotel	Sport shoes	TV
All countries	-0.01%	-0.05%	0.03%	-0.03%**	0.01%**
Czech Republic	-0.02%	-0.57%***	0.33%	0.02%	0.01%
France	-0.04%	-0.05%	-0.05%	-0.07%	0.01%
Germany	-0.01%	0.63%***	-0.03%	-0.20%***	-0.02%
Poland	0.12%***	0.04%	0.44%***	0.06%***	0.01%*
Romania	0.10%***	0.58%**	0.12%	0.00%	0.00%
Spain	0.01%	0.37%	-0.23%***	0.03%	0.07%***
Sweden	-0.12%***	-0.42%***	-0.14%	0.00%*	0.03%
United Kingdom	-0.06%***	-0.14%***	-0.05%**	-0.06%*	0.00%*

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. Two-sided mean comparison t-test was used.

Sample sizes: All products and all countries: 34,403 product matches.

By product: 6031-10,184 product matches (varies by product) By country: 3,506-5,014 product matches (varies by country)

By country and product: 472-1,502 product matches (varies by product and country)

Source: London Economics' analysis of mystery shopping data

The data suggests that in general, there are very small price differences in matched product pairs, and price differences are symmetric around the value of zero i.e. small price differences in both positive and negative directions.

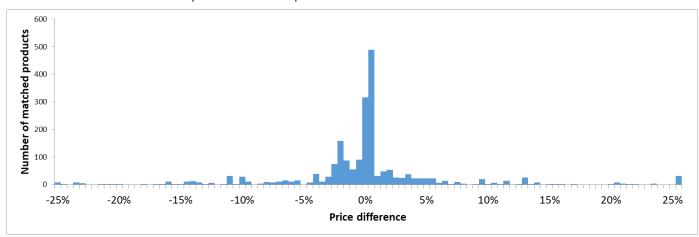
Of all 34,403 product matches, 94% show no price difference at all. The remaining 6% of differently priced products are not evenly distributed across product categories. The share of product matches with non-zero price differences is 14% and 7% in the airline ticket and hotel sectors, respectively, and 3% in both the sport shoes and TV sectors. The following histograms show the relative frequencies of non-zero values of the recorded price differences.

Three patterns emerge. Firstly, in all sectors, an overwhelming majority of the price differences are small (within $\pm 5\%$ bracket). Secondly, the price differences are relatively evenly distributed around zero. On average, positive and negative price differences mostly cancel each other out, leading to even smaller net results.

Thirdly, there are notable differences between goods and services. A larger share of observed airline ticket (14%) and hotel (7%) matches display some price difference compared to sport shoes and TVs (3%). This is however partially due to more random noise (prices of service products change more often due to reasons other than personalisation, e.g. dynamic pricing or yield management meaning that as one moves closer to the dates, the remaining prices of seats in a plane go up). In addition, price differences of sport shoes and TVs are more tightly clustered around zero, with service products exhibiting considerably thicker tails i.e. more of a spread in their distribution of recorded price differences.

Graphical analysis of distributions therefore suggests that there is more price personalisation in the two examined services sectors. It is however prudent to keep in mind that there is also more noise in these sectors, which makes it more difficult to isolate and estimate personalised pricing.

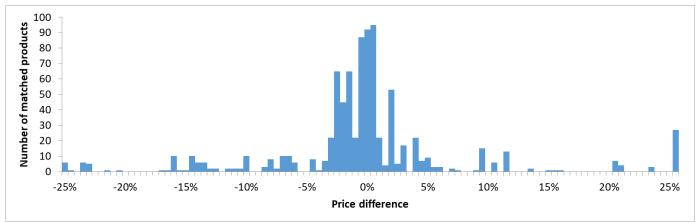
Figure 64: Histograms showing relative frequency of different values of the price difference between matched identical products. Zero price differences are omitted.



Sample size: 2061 product matches with non-zero price difference, representing 6% of all product matches.

Source: London Economics' analysis of mystery shopping data

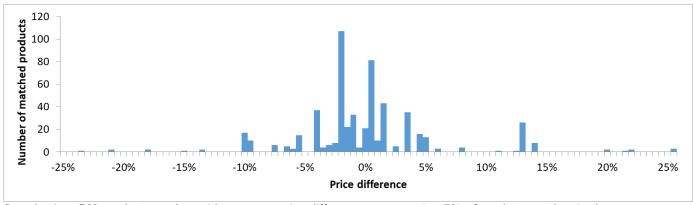
Figure 65: Histogram showing relative frequency of different values of the price difference between matched identical products in the airline ticket sector. Zero price differences are omitted.



Sample size: 853 product matches with non-zero price difference, representing 14% of product matches in the airline ticket category.

Source: London Economics' analysis of mystery shopping data

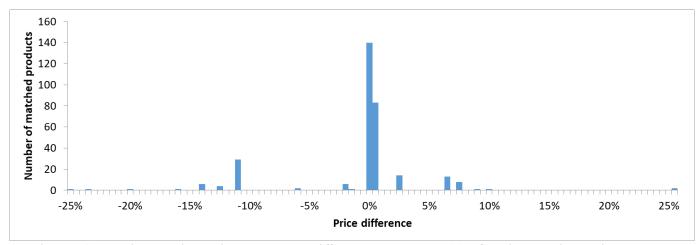
Figure 66 : Histogram showing relative frequency of different values of the price difference between matched identical products in the hotel sector. Zero price differences are omitted.



Sample size: 560 product matches with non-zero price difference, representing 7% of product matches in the hotel category.

Source: London Economics' analysis of mystery shopping data

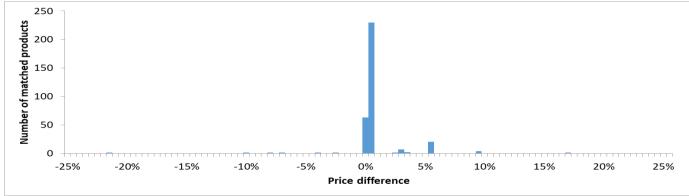
Figure 67: Histogram showing relative frequency of different values of the price difference between matched identical products in the sport shoes sector. Zero price differences are omitted.



Sample size: 314 product matches with non-zero price difference, representing 3% of product matches in the sport shoes category.

Source: London Economics' analysis of mystery shopping data

Figure 68: Histogram showing relative frequency of different values of the price difference between matched identical products in the TV sector. Zero price differences are omitted.



Sample size: 334 product matches with non-zero price difference, representing 3% of the product matches in the TV category.

Source: London Economics analysis of mystery shopping data

Personalisation scenarios compared to control shops, by type of personalisation

In general, it is possible that the analysis is unable to find strong evidence of price personalisation overall because different types of personalisation affect prices in opposite directions, leading to the small and statistically insignificant net effect. It is worthwhile therefore to study each personalisation scenario separately.

At the most detailed level of personalisation set-up, we can look at each step of each scenario. The scenarios varied the access route to the e-commerce website (e.g. search engine, PCW), while the steps within each scenario varied the e-commerce site's ability to observe the shopper's past online behaviour (see Table 54). Conducting the analysis separately for each step confirms very low price changes relative to the control shop and no statistically significant differences.

Table 54: Price personalisation, by type of shopper characteristic observable – comparison with the control shop

Steps compared	Percentage price difference
A1	-0.02%
A2	0.00%
A3	-0.01%
B1	-0.06%
B2	0.00%
C1	0.00%
C2	0.01%
C3	-0.01%
C4	0.01%
D1	0.00%
D2	-0.01%

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. Two-sided mean comparison t-test was used.

Sample sizes: 2003-2844 (varies by step)

Source: LE Europe

Once again, it is possible that small aggregate effects result from price personalisation acting in opposite directions in different sectors or countries, cancelling out on average. Therefore, we present results broken down by sector and country.

Breaking these results down by sector, we indeed find that within a given sector, different personalisation types affect prices in opposite directions. This is particularly the case in scenario B (PCW). While access through a PCW is associated on average with a 0.94% cheaper airline ticket, it is linked to more expensive prices of the other three products (though only the result for airline tickets is statistically significant). By contrast, airline tickets are 0.05% more expensive when purchased through a mobile device.

Table 55: Price personalisation compared to control shop, by product category

Product	Search engine (A)	Price Comparison Website (B1)	Internet browser (C)	Mobile device (D)
Airline ticket	0.02%	-0.94%*	0.01%	0.05%**
Hotel	-0.02%	0.36%	0.03%	-0.07%
Sport shoes	-0.04%*	0.01%	-0.05%*	-0.01%
TV	0.01%*	0.04%	0.02%**	0.00%

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. Two-sided mean comparison t-test was used.

Sample sizes: 330-649 in scenario B, 1847-3205 in others (varies by scenario and product category)

Source: LE Europe

Hence, breaking down results by personalisation type and product category also demonstrates that price differences are consistently small across disaggregated categories.

This result is confirmed also when disaggregating by country. The average price difference is smaller than 1% (in either direction) for all personalisation scenarios, in all countries. The largest differences are recorded in scenario B (PCW), but the sign varies by country. Access through a PCW is associated with statistically significantly lower prices in Sweden, but higher prices in Poland, Romania and the UK.

Table 56: Price personalisation compared to control shop, by country

Country	Search engine (A)	Price Compariso n Website (B1)	Internet browser (C)	Mobile device (D)
Czech Republic	0.01%*	-0.42%	-0.02%	0.04%
France	-0.06%*	-0.29%	0.02%	0.02%
Germany	0.06%	0.01%	-0.05%*	-0.09%**
Poland	0.10%	0.19%**	0.15%***	0.09%*
Romania	0.05%	0.71%*	0.00%	0.00%
Spain	0.02%	-0.21%	0.09%	0.00%
Sweden	-0.17%***	-0.37%*	-0.07%	-0.01%***
United Kingdom	-0.06%***	0.25%*	-0.07%***	-0.13%***

Note: Asterisks denote the result is statistically significantly higher than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample sizes: 168-338 in Scenario B, 773-1601 in others (varies by scenario and country)

Source: LE Europe

Personalisation scenarios compared to control steps

In the control steps, shoppers use the same technology and referral route when accessing the e-commerce website but switch to private browsing, which prevents the website from tracking the shopper's behaviour using cookies. The control steps therefore isolate price personalisation based on the information websites have about the shopper's past online behaviour (search history, purchase history etc.).

We find no overall statistically significant price differences between personalised steps and their respective control steps. The only significant difference is between step B1 (PCW) and the control step B2. However, unlike other control steps, step B2 not only disabled tracking but also varied the access route to the website. The control step therefore did not isolate the effect of cookies, but also includes the effect of PCW referral.

At the sector-level, however, the control step is significantly different in the airline sector both in scenario C (browser) and D. In C4, the prices of airline tickets were on average a little lower (-0.03%) than in C3 (where the shopper uses a browser they do not typically use). In D2, by contrast, the prices of airline tickets were slightly more expensive (0.02%) than in D1 (mobile device access).

At country-level, the only significant result was that products shopped in the Czech Republic were found more expensive in A1 (personalisation based on the preferred search engine) than in the three control steps (A2, A3, A4) by 0.04%. The difference between A1

and the control shop is also statistically significant, but the differences between A2, A3 and A4 compared to the control shop are not. This would suggest that the price personalisation recorded in A1 was already screened off in the control steps, in which the shopper used incognito browsing or a search engine that doesn't track them. This implies that the price personalisation employed by the e-commerce websites relied on past online behaviour of the shopper (rather than technology used to access the e-commerce website or the referral route).

Personalisation scenarios compared to each other

While the control steps were designed to isolate effects of personalisation based on the shopper's tracked online behaviour, the scenarios varied the access route of the shopper to the e-commerce website. Comparing either the personalised steps *between* scenarios (e.g. A1 against B1) or the control steps between scenarios (e.g. A3 against D2) can isolate the effect of the referral route or technology accessed.⁴⁰⁷ For example, comparing prices in A3 and C2 (incognito modes) should reveal differences between personalisation based on search engine referral and direct access to the website through URL.

Performing this analysis, we find no price differences exceeding statistical error at the aggregate level, but a number of results emerge from country- and product-level analysis. We present the statistically significant results below.

In the category of hotels, there was a statistically significant difference between D2 (mobile device, incognito browsing) and A2 (search engine that doesn't track users, desktop/laptop); and between D2 and C4 (alternative browser, incognito browsing, desktop/laptop) and D1 (preferred browser, mobile device) and C1 (preferred browser, desktop/laptop). In all cases, using a mobile device led to lower prices, by 0.16%, 0.20%, and 0.11% respectively.

Table 57: Price personalisation compared between steps with different types of personalisation, by product

Steps compared	Product	Percentage price difference
A2 v D2	Hotel	0.16%*
C4 v D2	Hotel	0.20%**
C1 v D1	Hotel	0.11%*

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. Two-sided mean comparison t-test was used. Only statistically significant results are

Sample sizes: 599-646 product matches

Source: London Economics analysis of mystery shopping data

At the level of countries, several differences were observed in France, Sweden, the UK, and the Czech Republic. The differences in most cases relate to prices observed when accessing an e-commerce website through a price comparison website (PCW).

In France, observations in Scenario B (PCW) were notably more expensive than in the other scenarios – access to a website through a PCW led to 1.7% higher prices than through direct (URL) access or search engine query, and to 1.8% higher prices than if accessed through a mobile device browser.

Similarly, in the UK, PCW referral led to 0.6%, 0.6% and 0.7% higher prices than if the website was accessed directly, through a search engine and through a mobile device,

⁴⁰⁷ Control step B2 cannot be used because it both blocked tracking and varied access route to website compared to step B1

respectively. In Sweden and the Czech Republic, the reverse was observed, with PCW access leading to 0.6% lower prices than direct access in Sweden and to 0.5% lower prices in the Czech Republic compared to access via the preferred browser on a mobile device. In addition, in Sweden, PCW access led to 0.9% lower prices than access through search engine and 0.9% lower than mobile device access.

Two further statistically significant price differences can be observed, though both are very small in magnitude. Access through a search engine led to slightly higher (0.04%) prices in the Czech Republic compared to direct access. In the UK, direct access through desktop/laptop led to 0.12% higher prices than access through mobile device.

Table 58: Price personalisation compared between steps with different types of personalisation, by country

Steps compared	Country	Percentage price difference
	France	-1.65%***
A1 v B1	Sweden	0.88%***
	UK	-0.59%**
A1 v C1	Czech Republic	0.04%*
B1 v C1	Czech Republic	-0.52%**
	France	1.73%***
	Sweden	-0.56%***
	UK	0.59%**
	Czech Republic	-0.53%**
	France	1.82%***
B1 v D1	Sweden	-0.90%***
	UK	0.70%**
	Poland	-0.49%*
C2 v D2	UK	0.12%***

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. Two-sided mean comparison t-test was used. Only statistically significant results are shown.

Sample sizes: 184-403 product matches

Source: London Economics analysis of mystery shopping data

Personalisation scenarios compared to control shops, by website

The above analysis has shown that, on average, prices observed by mystery shoppers were in most cases not significantly higher or lower when the e-commerce website could observe the shoppers' characteristics than when it couldn't. This absence of statistically significant results was usually consistent at the more disaggregated level of product categories, countries, or when varying the observable characteristics (e.g. search engine, browser, PCW, mobile devices).

In other words, the analysis did not find strong evidence that e-commerce websites in specific sectors, countries, or on the basis of specific sources of shopper information,

systematically increase or decrease prices when they are able to observe the consumers' personal characteristics.

This section looks at website-level data to investigate whether specific websites consistently increase or decrease prices when they can observe shopper characteristics.

As described earlier, the analysis finds 20-384 product matches per website. Therefore, it is possible for us to conduct statistical significance tests with the majority of the websites⁴⁰⁸, statistically comparing each website's average price difference to the baseline variation of its sector.

The mystery shopping data suggests that across all types of personalisation:

- On 7 websites (out of 153) prices are higher on average by more than 1% when shopper characteristics (either access route or past online behaviour e.g. browsing history due to online behaviour) are observable. The highest observed price difference in the positive direction is 3.9%
- On 6 websites prices are more than 1% cheaper on average when shopper characteristics are observable. The highest observed price direction in the negative direction is -2.84%.

It appears that the majority of websites do not consistently increase or decrease prices if they can observe shopper characteristics.

5.1.4. Pricing of personalised offers

With some exceptions, the analysis based on the mystery shopping data was unable to find robust evidence that e-commerce websites systematically increase or decrease prices of identical products when they can observe shopper characteristics. However, results may change if products are allowed to vary as well as price. 409

The results on offer personalisation based on the mystery shopping data, indicate that e-commerce websites personalise product offers for their customers, based on both browsing history as well other characteristics e.g. mobile device, browser etc. The similarity index, however, could not be used to determine if such personalisation benefits or harms the consumer.

The reason the similarity index cannot be used to assess the welfare impacts of personalised ranking of offers is because consumer welfare can be affected by both the product price and the quality of the product (i.e. does the product match the consumers personal preferences or needs). Even if a consumer pays more for a product the product may be a better match for them , as such the similarity index by itself cannot measure the consumer welfare impact of offer personalisation.

While it is not possible to use the similarity index, personalised ranking of offers is measured (instead) by studying the difference in the total price of top-ranked products in the mystery shopping scenarios, as compared to the price of top-ranked products in the control shop. Note that both price and offer personalisation can affect the price difference. However, given that the research concludes that price personalisation is on average not statistically significant, large and statistically significant results in the combined effect will be attributable to offer personalisation.

⁴⁰⁸ Three websites with fewer than 50 product matches are excluded. Fewer product matches than 50 would be too small a sample to perform statistical tests on.

⁴⁰⁹ The analysis of personalised pricing was based on matching identical products and testing if there were price differences based on the mystery shopping scenarios.

Caveats of using the combined effects of personalised pricing and offers to estimate welfare impacts

It is important to keep in mind the caveats of combining offer and price personalisation. Firstly, offer personalisation also affects welfare in other ways than price. For example, it could reduce the consumer's search costs by showing them the products that are more likely to match their preferences. For example, participants in the behavioural experiment frequently indicated that they liked personalisation because they would be shown offers that matched their needs (see Section 6).

Secondly, the approach does not control for the quality of the products offered. So even if a higher average price is found, quality-adjusted price might be unaffected.

Thirdly, consumer welfare would be affected only if product ranking actually impacted consumers' purchase choices. The behavioural experiment, in line with previous research (e.g. FCA 2015^{410}), indicates that consumers frequently tend to select the top-ranked product. However, again, personalisation could steer consumers towards products that they feel match their needs.

Overall the approach can identify whether the top ranked products have higher prices when sellers can observe consumer characteristics, but it cannot determine the overall consumer welfare effect.

Results of the mystery shopping exercise

Similar to the previous section on product differences, no statistically significant price differences are found in any of the mystery shopping scenarios. The total price of 5 top-ranked products – averaged across all shops – is not statistically significantly different from the average price of 5 top-ranked products in the control shop. Across all product categories, the analysis did not find evidence that would suggest that e-commerce websites systematically display more or less expensive products to consumers when they could observe consumer characteristics (e.g. browsing history or access route to the website).

Unlike the previous section, however, disaggregated product-level analysis found some statistically significant results. Nevertheless, in all cases, the price differences are small. In scenario A, C and D, the 5 top-ranked TVs were on average 0.5%, 0.6% and 1.3% cheaper than in the control shop, respectively. (See Table 59). In addition, 5 top-ranked sport shoes offered in Scenario C were 0.3% cheaper than in the control shop. The only product category more expensive in the personalised scenarios were airline tickets in Scenario D and C. When accessing the e-commerce website using their mobile device, shoppers observed flight tickets that were on average 0.75% more expensive than in the control shop; when accessing the website directly, they were 0.80% more expensive than in the control shop.

⁴¹⁰ FCA (2015), High Cost Short Term Credit Price Comparison Websites.

⁴¹¹ The analysis was also conducted for the top two ranked products. The same results were found as in the case of the top five ranked products.

Table 59: Combined effect of personalised offers and pricing, by product

Product	Search engine (A1)	Price Comparison Website (B1)	Internet browser (C1)	Mobile device (D1)
Airline ticket	0.43%	-0.32%	0.80%*	0.75%**
Hotel	0.71%	1.44%	1.42%	0.88%
Sport shoes	-0.32%	-0.39%	-0.33%*	-0.34%
TV	-0.52%**	1.36%	-0.61%**	-1.31%**

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used.

Sample size: 101-173 shops (varies by scenario and product category)

Source: London Economics analysis of mystery shopping data

Country-level disaggregation finds only one statistically significant result, Scenario A in Romania.

Table 60: Combined effect of personalised offers and pricing, by country

Country	Search engine (A1)	Price Comparison Website (B1)	Internet browser (C1)	Mobile device (D1)
Czech Republic	0.25%	-0.80%	0.28%	0.32%
France	-0.63%	3.06%	-0.93%	-0.96%
Germany	-0.30%	0.40%	0.17%	0.34%
Poland	0.80%	-4.88%	0.66%	-1.39%
Romania	0.61%*	1.07%	1.51%	0.61%
Spain	0.29%	-0.39%	0.24%	0.07%
Sweden	-0.90%	-0.18%	0.33%	0.82%
United Kingdom	0.40%	4.34%	0.33%	0.00%

Note: Asterisks denote the result is statistically significantly lower than the baseline at *95% confidence level, **99% and ***99.9%. Two-sided mean comparison t-test was used.

Sample size: 42-88 shops (varies by scenario and country)

Source: London Economics analysis of mystery shopping data

Therefore, the mystery shopping does not find statistically significant evidence that personalisation is linked to significantly different prices for the steered products for consumers overall, or systematically in any sector or country.

Price differences of personalised offers

Even when the products are allowed to vary, the analysis shows no significant price differences between the situation where the shopper's characteristics are observable and when they are not. It is possible, however, that some characteristics lead to personalisation towards more expensive products, while other characteristics lead to cheaper products, resulting in the statistically insignificant net effect.

This section combines the mystery shopping data with socio-demographic characteristics of the shoppers to investigate whether different characteristics lead to personalisation in opposite directions. Specifically, the prices of the top 5 products observed by shoppers who report they usually buy "discount" products are compared with the prices observed by shoppers who say they usually shop for "high-end" products.

The analysis⁴¹² was performed at product category level. For each step in each scenario, the analysis proceeded as follows:

- For each shop, find the total price of the 5 top-ranked products
- Find the total price of the 5 top-ranked products in the corresponding control shop
- For each shop, compute the percentage difference between the two
- Find the average percentage difference across shoppers who reported that they
 usually shop for "discount" products⁴¹³ in the given product category
- Find the average percentage difference across shoppers who reported that they usually shop for "high-end" products in the given product category
- Statistically compare the two averages

These tests were unable to reject the null hypothesis of no difference. Therefore, the analysis based on the mystery shopping data did not find evidence that e-commerce websites use personalisation based on shoppers' observable characteristics to steer them towards products of different price.⁴¹⁴

However, we note that these results do not necessarily indicate that e-commerce websites do not steer consumers towards products with different price. As stated before, the tests conducted have a relatively low power, since sectoral-level analysis reduces the sample size available considerably. A further problem could be the fact that shoppers self-reported as 'discount' or 'high-end'. This is a subjective assessment, therefore the categories may not always pick up on whether shoppers would truly be steered towards less or more expensive products.

5.1.5. Personalisation based on access via Price Comparison Website (PCW)

The analysis of the incidence of personalised offers and pricing suggested that websites frequently personalise based on whether shoppers access the website through a PCW. The impact of accessing a website via a PCW tended to be stronger than other mystery shopping scenarios (see Section 5.1.1, 5.1.2 and 5.1.3).

Therefore, this Section examines personalisation through PCW access in more detail.

⁴¹² For an overview of methodological choices (values omitted in the analysis etc.), refer to the Annex

⁴¹³ The shoppers assessed this on a scale from 0 ("discount") to 10 ("high-end"). The analysis compares shoppers who reported a score of 5 or lower with those who reported 6 or higher. Sensitivity analysis around the threshold showed that alternative thresholds lead to same results (i.e. absence thereof).

⁴¹⁴ The only test that found statistically significant difference (at 95% confidence level) between the "discount" and "high-end" shoppers was for hotels in step C1 (preferred browser, direct website access). The result counterintuitively suggests that "discount" shoppers were shown hotels that were on average 5% more expensive. This finding however does not consistently emerge from the data. No other result for hotels is statistically significant. Moreover, in most other scenarios, the average price paid by "discount" shoppers for hotels was actually lower than the price paid by "high-end" shoppers.

⁴¹⁵ The shoppers reported whether they shop for "discount" or "high-end" products separately for each sector.

Economic theory suggests two main effects, operating in opposite directions, that may contribute to offer and price personalisation when shoppers access a website through a PCW:

- Shoppers may be shown different products, or face lower prices because of price discrimination: shoppers who use PCWs may be perceived as more price-sensitive. Therefore, e-commerce websites may price-discriminate, offering these consumers lower prices;
- However, there may be an upward pressure on shoppers' prices because of commercial relationships between e-commerce websites and PCWs: if PCWs charge e-commerce websites for their products to be prominently featured, e-commerce websites may be in a position to pass through their higher costs to consumers who use PCWs to access their websites. However, the ability of e-commerce websites to pass through costs would be limited by shoppers' price-sensitivity and ability to compare deals and shop around.

Previous research by Mikians et al. (2012)⁴¹⁶ finds evidence that the first effect (reducing prices) may be stronger i.e. access through a PCW leads to lower prices. The study examined prices of products in 25 product categories on a specific price comparison website, comparing these to prices observed when visiting the website directly. Mikians et al. (2012) found two websites that return lower prices when shoppers visit the e-commerce website though a PCW, compared to visiting the website directly. Across the products where a price difference is observed, the average price difference was 24%.

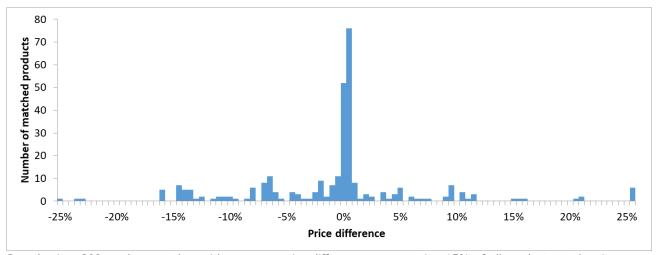
The mystery shopping data also suggests greater evidence of price personalisation when shoppers access a website through a PCW, although the price differences are considerably smaller. While the overall average price difference (in absolute values) in the other scenarios varied from 0.15% to 0.22%, prices of products in the PCW scenario differed on average by 0.77% relative to the control shop (see Table 47).

At the most detailed level of personalisation set-up, we can look at each step of each scenario. The scenarios varied the access route to the e-commerce website (e.g. search engine, PCW...), while the steps within each scenario varied the e-commerce site's ability to observe the shopper's past online behaviour (see Table 31). Table 47 shows average price personalisation for each step. The largest average price difference compared to the control products (0.77%) was observed in step B1, in which the mystery shopper accessed the e-commerce website through a PCW. Section 5.1.5 looks more closely at personalisation based on a referral from a PCW.

Price personalisation was particularly strong in the airline sector. When accessing an e-commerce website through a PCW, shoppers saw on average prices different by 3.41% compared to the control shop (in absolute values, see Table 48). By contrast, in the other scenarios, the price difference was almost 90% smaller: varying from 0.35% to 0.55%.

⁴¹⁶ Mikians, J. et al (2012). Detecting price and search discrimination on the Internet. Available <u>here</u>.
⁴¹⁷ One reason for this difference is that our analysis finds the average difference by averaging all observed product matches, not excluding matches with zero price difference. If matches with zero difference are excluded, the average difference in absolute values is 5.2% (and the net difference is -3.8%). Our analysis also looked at more PCWs (Mikians et al. only studied data from the one PCW where they found strongest results).

Figure 69: Histogram showing non-zero price differences of products observed when comparing the PCW scenario with the control shop



Sample size: 299 product matches with non-zero price difference, representing 15% of all product matches in the PCW scenario.

Source: London Economics analysis of mystery shopping data

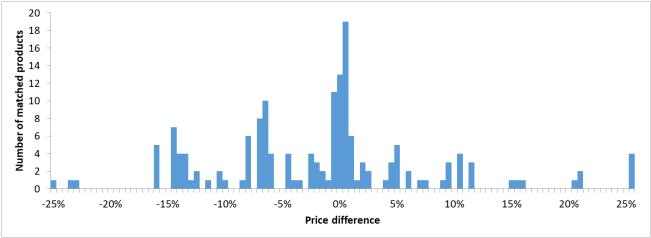
Price personalisation via PCW access remains particularly large in the airline ticket sector, even when we take the presence of cookies into account by directly comparing the PCW scenario with the other personalised scenarios (see Table 52 for details).

On average, PCW access leads to airline ticket prices that are different by 4.8% compared to access via search engine; 4.4% compared to direct URL access; and 4.8% compared to mobile device access. This is the largest price difference observed in the mystery shopping data. In the case of shoes and TVs, no price difference was statistically significant. In the case of hotels, the only significant result is that PCW access led to different prices by 0.5% compared to search engine.

The mystery shopping data also backs up Mikians et al (2012) in finding that access through PCWs lowers prices, with the largest significant price reductions observed for airline tickets again in many countries. Airline tickets are, on average, 0.94% cheaper in the PCW scenario compared to the control shop (and this result is statistically significant, see Table 55). By contrast, in the other scenarios, airline ticket prices are on average larger than or not significantly different from the control shop.

Absolute average price differences are considerably larger than net average price differences. One reason for this is that shoppers who accessed e-commerce websites through PCWs were sometimes shown higher prices compared to shoppers who accessed the website directly (as shown in the figure below). To understand this effect better, we again look at direct comparisons between scenarios, which isolates the price effect of PCW referral.

Figure 70 : Histogram showing non-zero price differences of airline tickets observed when comparing the PCW scenario with the control shop



Sample size: 164 product matches, representing 55% of all matches non-zero price difference in the PCW scenario **Source: London Economics analysis of mystery shopping data**

Interestingly, in the airline sector, there is no statistically significant net difference between PCW access and access through search engine, browser, or mobile device (Table 61). This is because PCW access leads to lower airline ticket prices in some countries, higher in others and the two effects nearly cancel each other out on average (see Table 62).

Table 61: Price personalisation in the airline ticket sector compared between steps with different types of personalisation

Airline tickets	Baseline variation	B1 (PCW) v control shop	B1 (PCW) v A1 (search engine)	B1 (PCW) v C1 (browser)	B1 (PCW) v D1 (mobile device)
Price difference in absolute values	0.13%	3.41%***	4.77%***	4.36%***	4.83%***
Net price difference	0.00%	-0.94%*	-0.36%	-0.31%	-0.76%

Note: Asterisks denote the result is statistically significantly higher than/different from the baseline at *95% confidence level, **99% and ***99.9%. One-sided mean comparison t-test was used for absolute values; two-sided for net price differences.

Sample sizes: (varies by scenario)

Source: London Economics analysis of mystery shopping data

The data suggest that while in the Czech Republic, Poland, and Sweden access via PCW leads to airline ticket prices lower by 3-9%, in the UK and France the average price actually increases by 2-15%.

 $^{^{418}}$ We note that at this level of disaggregation (6-24 observations), it is no longer possible to conduct statistical tests.

Table 62: Net price personalisation in the airline ticket sector compared between scenarios, by country

Country	B1 v A1	B1 v C1	B1 v D1
Czech Republic	-5.23%	-6.36%	-7.05%
France	14.88%	14.56%	11.12%
Germany	-0.90%	0.06%	-0.44%
Poland	-6.34%	-9.35%	-7.76%
Romania	-0.16%	-0.13%	-0.48%
Spain	-1.65%	-2.72%	-0.87%
Sweden	-3.56%	-2.68%	-3.90%
United Kingdom	2.72%	2.42%	2.89%

Note: Asterisks denote the result is statistically significantly different from the baseline at *95% confidence level, **99% and ***99.9%. Two-sided mean comparison t-test was used.

Sample sizes: 6-24 (varies by scenario and country)

Source: London Economics analysis of mystery shopping data

Another reason that access through PCWs may affect prices, is that e-commerce websites may also personalise offers based on PCW referral.

The PCW scenario had an average offer similarity index relative to the control shop of 0.78 (see Table 32), which showed evidence of significantly different offers relative to the control shop. Moreover, the PCW scenario showed one of the highest offer variations relative to other scenarios (see Table 42). This was driven mostly by the airline ticket and hotel sectors (see Table 43).

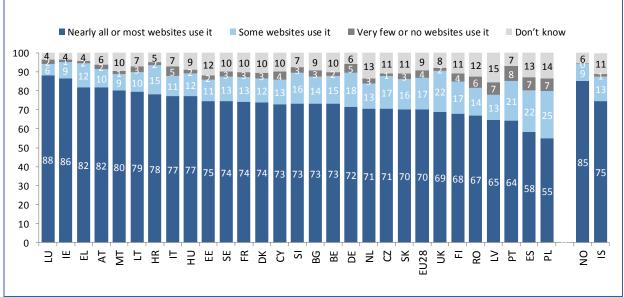
A small sample size and the lack of clear and geographically consistent results in the PCW scenario inhibits any strong conclusions. However, both the evidence from Mikians et al. (2012) and the mystery shopping data suggest that accessing a website via PCW influences prices. Moreover, these differences seem to be considerably more pronounced than results based on other sources of personalisation, particularly in the airline ticket sector. However, further research is needed to illuminate the issue.

5.2. Perceived incidence of personalised practices

5.2.1. Findings from the consumer survey

To explore how often consumers *believe* to be exposed to online personalised practices, respondents in the *consumer survey* were asked how widespread they thought the three main personalisation methods covered by study are. Across the EU28, more than two thirds (70%) of respondents reported that in their experience nearly all or most websites use *online targeted advertising*. This figure varied substantially between countries: whilst on one end of the country ranking nearly nine out of ten (88%) of respondents in Luxembourg thought that nearly all or most websites use online targeted advertising, on the other end of the country ranking in Poland, only slightly more than half (55%) of respondents thought the same.

Figure 71: Perceived incidence of online targeted advertising, split by country



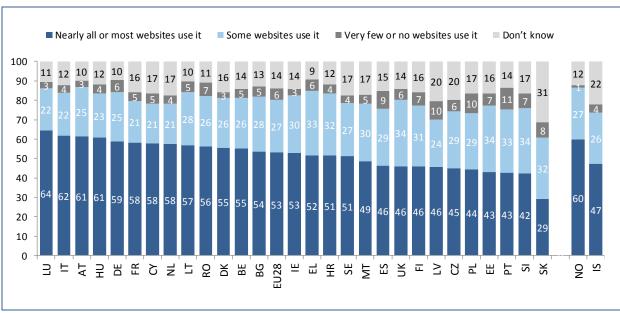
Q6. Based on your experience, how widespread do you think that online targeted advertising is?

%, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

On average, respondents thought that *online personalised ranking of offers* are less widespread than online targeted adverts. Across the EU28, slightly more than half (53%) of respondents thought that nearly all or most websites use online personalised ranking of offers. This figure varied between 64% in Luxembourg and 29% in Slovakia.

Figure 72: Perceived incidence of online personalised ranking of offers, split by country



Q11. How widespread do you think that online personalised offers are?

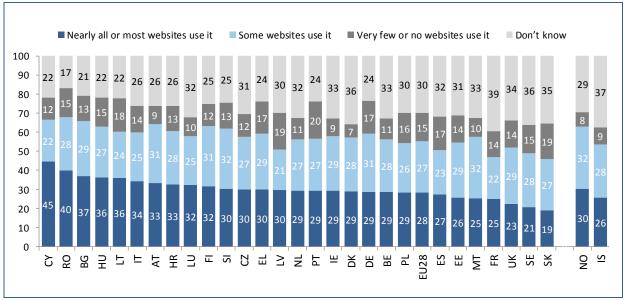
Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513

Source: Consumer survey

Across the EU28, only slightly more than a quarter (28%) of respondents reported that in their experience, nearly all or most websites use *online personalised pricing*; this figure varied between 45% in Cyprus and 19% in Slovakia. When looking at the perceived incidence of personalised pricing, it is worth noting that almost a third (30%) of respondents in the EU28 indicated that they did not know how widespread this form of personalisation is. This is clearly higher than the proportion of those who answered "don't know" to the similar questions on online targeted adverts and personalised ranking of offers

(for these two personalised practices, 9% and 14% of respondents mentioned that they did not know how widespread these practices are, respectively). This aligns with the figures about awareness presented in Chapter 4, which show a relatively lower awareness of personalised pricing.

Figure 73: Perceived incidence of online personalised pricing, split by country



Q16. How widespread do you think that online personalised pricing is?

%, by country, Base: All respondents (EU28: n=21,734; NO: n=803; IS: n=513)

Source: Consumer survey

The perceived incidence of the three personalisation practices differed little across socio-demographic groups or between the EU15 and EU13 regions. In line with the question about awareness shown in Chapter 4, respondents who buy online most frequently were more likely than those who never do so to indicate that nearly all or most websites use personalised practices.

Table 63: Perceived incidence of personalised practices, split by socio-demographic group

			,				
	Base (EU28)	Q6. Based on your experience, how widespread do you think that online targeted advertising is?	you think that online personalised offers are?	Q16. How widespread do you think that online personalised pricing is?			
		Net: Nearly	all or most wel				
Average (EU28)	21,734	70%	53%	28%			
EU Region	11.000	740/	E 40/	2004			
EU15	11,832	71%	54%				
EU13	9,902	66%	48%	32%			
Age							
16-34	8,196	72%	51%				
35-54	9,170	69%	53%				
55-64	2,992	70%					
65+	1,376	68%	56%	30%			
Gender							
Male	10,959	70%					
Female	10,775	71%	54%	27%			
Working status							
Employed	12,413	70%					
Self-Employed	1,713	74%	54%				
Unemployed but looking for a job Unemployed & not looking for a job + other non-active*	1,416 3,961	68%	50%				
Pupil / Student / In education	2,231	75%	51%	28%			
Living area							
Large town or city	8,145	72%	55%	31%			
Small or medium sized town	8,474	69%	53%	27%			
Rural area or village	5,115	70%	52%	26%			
Education							
Low	2,250	61%	48%	27%			
Medium	9,506	69%	55%	29%			
High	9,978	74%	53%	28%			
Household financial situation							
Very easy	1,727	73%	55%	28%			
Fairly easy	9,277	71%	53%	29%			
Fairly difficult	7,953	69%	53%	28%			
Very difficult	1,988	68%	53%	28%			
Buy goods and services online							
Once a week or more often	4,944	74%	58%	32%			
Once a month or more often	8,500	72%	54%	28%			
Once every three months or more often	4,943	68%	51%	26%			
Once in the last 12 months or more often	2,317	65%	51%	28%			
Never	1,030	49%					
* Sick/disabled, Housewife/homemaker		73 70	33 70	22 70			
Sicky disabled, Housewite/HorrielHakel	, Neureu						

Source: Consumer survey

5.3. Findings from the stakeholder survey on the incidence of personalised practices

Respondents in the stakeholder surveys were asked which personalisation practices they believed to be most common in the online market. One see in the figure below the results for all stakeholder groups combined.

Targeted advertising is the most widespread practice according to stakeholders: in total, 15 out of 28 (54%) respondents reported that this practice is in their opinion used by 'most websites' or 'nearly all websites', whereas a further 4 respondents (14%) reported that they think 'some websites' use this personalisation practice. The usage of **targeted emails** is also widespread, according to the stakeholders consulted: 11 out of 29 stakeholder (38%) respondents noted that nearly all or most websites use targeted emails. Another 9 stakeholders (31%) indicated that some websites use this practice. About a fifth (5 out of 28) of respondents indicated that in their opinion 'most websites' use **targeted discounts** yehilst a further 12 respondents (43%) mentioned that they believe 'some websites' make use of this practice.

When asked about *personalised ranking of offers* (price steering), 9 out of 28 (32%) respondents reported that some websites use this practice, while only 1 stakeholder (4%) thought that most websites use this practice. Three stakeholders (out of the 28) thought that websites do *not* use personalised offers at all. It should be noted that most stakeholders (15 out of 28) reported not to be aware/ don't know about personalised offers. As noted in Chapter 2, this might be due to the low awareness about the subject, the fact that online personalisation practices are a relatively new phenomenon resulting from technological advances. Furthermore, the study findings show that detectability of personalisation practices, especially personalised pricing is in general low.

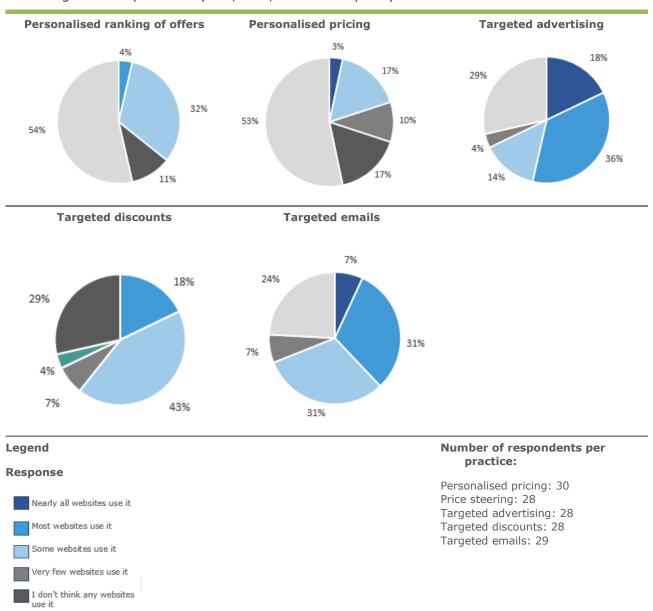
Only 1 stakeholder indicated that 'nearly all websites' use **personalised pricing**, whereas a further 5 out of the 30 (17%) replied to this question that 'some' websites use personalised pricing. Another 8 (27%) respondents from the stakeholder survey mentioned that very few or no websites use personalised pricing. About half (53%) indicated that they did not know to what extend personalised pricing is employed by online business operators.

Interviewed national experts noted that personalised pricing is a practice used by online business operators, but that it is difficult to quantify as, many retailers avoid overtly using this practice, as they would risk losing their customers.

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⁴¹⁹ A form of personalised offers where special discounts are set to certain consumer groups, e.g. students, elderly etc.

Figure 74: The most prevalent personalisation practices used by online business operators according to all respondents (CPA, DPA, National Experts)



Q6. According to your information, which personalised pricing/offers practices are employed by online business operators in your country and how widespread do you estimate these to be?

Source: All stakeholder surveys (DPAs, CPAs, national experts)

Don't know

DPAs, CPAs and national experts reported in the stakeholder survey that in their opinion personalised practices are most common for holiday accommodation (reported by 14 out of 30 respondents), clothes/footwear (13 out of 30) and travel services (12 out of 30). Electronics and computer hardware followed only in the 7th position, according to the stakeholders. For detailed results, please see Annex 3.

5.4. Summary of results – Research on the incidence and magnitude of online personalised pricing/offers

Box 4: Summary of findings – Research on the incidence and magnitude of online personalised pricing/offers

Findings from the mystery shopping on personalised offers

- The mystery shopping found evidence of offer personalisation (i.e. changing the share of common products that have the same rank) both based on information about the shopper's past online behaviour (cookies, search history etc.) as well as on four different pieces of information about the shopper's access route to the website (search engine referral, price comparison website referral, browser used, device used).
- From the latter, access to an online retailer through a price comparison website or using a mobile device (as opposed to desktop) is shown to have the strongest impact on the ranking of offers, as opposed to access via a different browser or via a search engine.
- In particular in Polish, Swedish, British and Romanian e-commerce websites more extensive personalisation of offers was detected. Among 4 product categories, significantly more personalisation of the ranking of offers was detected in airline ticket and hotel offers than for shoes and TVs.
- In over three fifths of e-commerce websites (61%) personalisation of offers was detected in at least one of the parameters considered by the analysis (access route to the website including the type of browser or device and tracking of online behaviour), when compared to the control shop of no personalisation).
- E-commerce websites track their users in different ways. Therefore, while relatively few websites may use one particular technique, relatively more websites use *any* of the personalisation parameters mentioned above.

There is stronger evidence for offer personalisation based on the access route to the website than on tracking the shopper's past online behaviour. The mystery shopping exercise suggests that 54% of websites in the sample personalise offers based on the access route, while 44% personalise offers using some information collected about the shopper's past behaviour.

Findings from the mystery shopping on *personalised pricing*

- The research method applied in the mystery shopping did not detect evidence of consistent and systematic price differences (price discrimination) between scenarios where the e-commerce website could observe shopper characteristics (either access route to the website or past online behaviour) and when it could not.
- Price differences that could not be explained entirely by random price variation were observed in 34 websites out of 153, but they are in most cases very small in magnitude and relatively evenly distributed around zero. Net price differences are statistically insignificant.
- Of the 34 websites showing price personalisation, 19 belong to the airline ticket sector (websites of platforms selling air tickets and not of airline companies as such), 9 to the hotel sector, 4 to the shoes sector and 2 to the TV sector
- The average difference exceeds 1% on 16 websites, with the largest average just under 4%. All of the 16 websites belong either to the airline ticket or hotel sectors
- Larger differences were found when comparing personalisation scenarios with each other than when comparing the scenarios to a control shop. In particular, in some countries, access to the website through a PCW is linked with a price difference of up to 3% on average compared to direct URL access or access through a search engine query.
- On 7 websites (out of 153) prices are higher on average by more than 1% when shopper characteristics are observable. On 6 websites prices are more than 1%

cheaper on average when shopper characteristics are observable. The website with the highest average difference in price recorded a 3.9% increase, while the largest decrease was -2.8%.

- In the sample, smaller websites appear to personalise prices on average more than larger websites. One reason for this may be that larger websites may be more likely to be scrutinised for evidence of price personalisation, and therefore larger websites may have a disincentive to personalise prices. Another reason may be that smaller websites in our sample are more sensitive to small traffic increases compared to larger websites, and therefore are observed to personalise more often due to the successive visits of the mystery shoppers.
- It should be noted that the mystery shopping results are based on a (non-random) sample of 160 websites across 4 product categories and 8 EU Member States and may not be representative for the EU e-commerce market as a whole.

Findings from the mystery shopping on the prices of personalised offers

- No evidence was found of systematic price differences of the offered top-ranked products (i.e. in case shoppers were offered different products).
- Some statistically significant but small results are found at the level of individual product categories. Access from a mobile device is linked to more expensive airline tickets, but cheaper sport shoes and TVs. Cheaper top-ranked TVs and more expensive airline tickets than in the control shop are also observed when the website is accessed directly, but the effect is very small.

Findings from the consumer survey and stakeholder survey

- Across the EU28, more than two thirds (71%) of respondents in the consumer survey reported that in their experience nearly all or most websites use online targeted advertising. For personalised ranking of offers and personalised pricing, this figure was 53% and 28%, respectively. For personalised pricing, one in three respondents could not provide an estimate for incidence.
- The stakeholders consulted believed that targeted advertising is the most common personalised practice: 15 out of 28 (54%) stakeholders reported that this practice is in their opinion used by 'most' or 'nearly all' websites. When asked about personalised offers, 9 out of 28 (32%) stakeholders reported that some websites use this practice. About half (53%) of stakeholders indicated that they did not know to what extend personalised pricing is employed by online business operators (similarly for personalised offers this was 54%), whilst another 8 (27%) mentioned that they think that very few or no websites use personalised pricing.

6. Influence of personalised pricing/offers on consumers' decisions and remedies

This chapter, which is based on findings from the behavioural experiment, looks at the influence of personalisation on consumers' decision-making, comprehension and feelings about personalisation. In addition, the chapter looks at the impact of communication transparency on consumers' decisions.

6.1. Brief summary of the experimental conditions

The design of the behavioural experiment is detailed in Annex A1.8. Here a re-cap of the experimental treatments is presented to assist with interpretation of the findings within this chapter.

The experiment tested whether participants' awareness, decision-making and feelings about personalisation varied according to the types of personalisation they experienced, as well as how transparently personalisation was communicated to them.

In the experiment, participants were randomly allocated to one of the following types of personalisation scenarios:

- The 'baseline' or 'no personalisation' scenario, where search results were presented randomly;
- Personalised ranking of offers where the ranking of offers was tailored to participants based on their previous search history or browser;
- Price discrimination where participants were shown either higher, or lower, prices for the same product depending on their previous search history; and
- Targeted advertising where participants were shown a targeted advertisement, combined with either random sorting of search results, or results sorted based on their previous search history.

The behavioural experiment also tested the impact of treatments varying how transparently personalisation was communicated to participants.

- Low transparency: where it was not made clear to the participant that results were personalised;
- High transparency: where participants received salient communication that results were personalised to them; and
- High transparency + action: where participants received salient communication of personalisation, and it was easier for them to clear cookies and search again by a one click button.

6.2. Decisions taken by participants in the behavioural experiment

The behavioural experiment simulated an online search platform. Participants could choose to undertake a number of actions in the experiment:

- purchase a product from the platform or to continue the experiment without purchasing;
- switch platforms;
- clear cookies and search again on the same platform.

Overall, slightly more than 70% of experiment participants chose to purchase a product in the experiment. Participants were more likely to purchase the products that were personalised to them under targeted advertising combined with personalised ranking, and price discrimination (when prices were lowered due to the discrimination) compared to the scenario of no personalisation. This effect was statistically significant in the low transparency treatment.

On average, 30% of participants chose to switch platforms in the experiment. Increased transparency of how personalisation was occurring on the website plus an easier process to clear cookies reduced the propensity for experiment participants to switch away from the site, compared to when the site did not clearly indicate that personalisation of offers was occurring. This finding indicates that when consumers are informed by websites that offers are being personalised based on previous purchases, they may feel re-assured by the site's transparency and that they are able to easily limit sellers' ability to personalise (should they wish to) by clearing cookies in a simple and salient one click step.

Increased transparency by websites about how products shown are being personalised and simplification of the clear cookies action, can lead to improved consumer choice online. Increased transparency can also benefit sellers as consumers may be more likely to stay with the site rather than switching to a competitor's site. Less than 3% of participants chose to clear cookies across all scenarios. However, participants were statistically significantly more likely to clear cookies in the high transparency plus action treatment, where the 'clear cookies' button was displayed more prominently and participants had to carry out less effort to clear cookies.

The following sections describe participants' actions in the behavioural experiment, as well as the reasons for their actions.

6.2.1. Whether participants chose to purchase products, by treatment, scenario and sociodemographic group

Overall, just over 72% of respondents chose to purchase a product in the experiment (Table 64). When comparing across all personalisation scenarios, respondents were most likely to purchase a product when the website clearly informed the respondent that personalisation was occurring and the respondent was able to clear their cookies using a one click button shown at the top of the screen (75.5% in high transparency + action treatment compared to 68.6% in the no personalisation baseline). The effect of personalisation on propensity to purchase in the experiment was however found not to be statistically significant overall.

Table 64: Proportion of participants purchasing products in the experiment, by scenario and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
No personalisation	68.6	-	-	-	68.6
Personalised ranking of offers: based on browser	-	71.3	70.3	76.7	72.8
Personalised ranking of offers: based on previous searches	-	73.3	77.8	73.4	74.8
Price discrimination: high prices	-	73.8	71.1	80.7	75.2

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
Price discrimination: low prices	-	67.8	63.4	68.2	66.5
Targeted advertising: random sorting of search results	-	71.3	69.5	75.1	72
Targeted advertising: personalised ranking of offers sorting of search results	-	70.9	77.8	78.8	75.8
Total	68.6	71.4	71.7	75.5	72.6

Note: This table displays the proportion of participants purchasing products across all 3 runs of the experiment **Source: London Economics analysis of online experiment data**

The experiment did not identify a statistical difference in respondents' propensity to purchase different products per sector (Table 65). Respondents were slightly less likely to purchase rental cars than televisions or holiday rentals but this difference was very small.

Table 65: Proportion of participants purchasing products in the experiment, by product and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Car rentals	62.4	69.2	68.9	76.1	70.9
N	100	595	591	593	1,879
TVs	69.4	74.8	73.6	76	74.5
N	123	744	740	743	2,350
Holiday rentals	73.6	70	72.3	74.5	72.3
N	123	747	739	742	2,351

Note: This table displays the proportion of participants purchasing products across all 3 runs of the experiment **Source: London Economics analysis of online experiment data**

Increased transparency by websites that personalisation is occurring may give consumers with less online experience more confidence in making an online purchase. Overall respondents who had less online experience were the least likely to make purchases in the experiment. However, when the website increased its transparency the likelihood that these respondents would make a purchase also increased from 56% in the low transparency treatment to 62.3% in the high transparency + action treatment (Table 66). The difference is statistically significant at 95%.

Table 66: Proportion of participants purchasing products in the experiment, by sociodemographic group, region and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Country group					
EU15	70.2	72.2	73.1	77.1	73.9
EU13	60.6	67	64.1	67.3	65.9
Age group					

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
16-34	76	75	75	78	76
35-54	63	69	69	75	70
55-64	69	68	72	69	70
65+	76	69	72	75	72
Gender					
Male	70	73	72	79	74
Female	67	70	72	72	71
Economic activity					
Active	71.6	73.4	71.5	75.6	73.4
Inactive	60.4	66.6	72	75.2	70.8
Educational attain	ment				
Medium/High	69.9	71.8	73.4	77.7	74.1
Low	61.8	68.6	60.5	62	63.5
Making ends meet					
Not difficult making ends meet	70.6	72.5	73.5	79.4	74.9
Difficult making ends meet	67.3	70.4	70.1	71.4	70.5
Experience with or	nline transaction	S			
Relatively experienced	72.8	73.1	72.7	77.1	74.2
Relatively inexperienced	46.2	56	63.3	62.3	59.6
N	156	943	950	921	2,970

Note: This table displays the high level actions taken across all 3 runs of the experiment. Participants are coded as finding it difficult to make ends meet if they indicate that they find it 'fairly difficult' or 'very difficult' to make ends meet

Participants are coded as 'relatively inexperienced' with online transactions if they indicate that they use the internet to buy goods/services online once in the last 12 months, or less frequently.

Source: London Economics analysis of online experiment data

Participants' beliefs about whether personalisation had occurred had little impact on whether they purchased a product. The figure below indicates that there was no significant difference in the proportion of participants purchasing products between those who believed that personalisation had occurred and those who did not. Approximately 70% of participants purchased products in the behavioural experiment, irrespective of whether they believed personalisation had occurred or not.

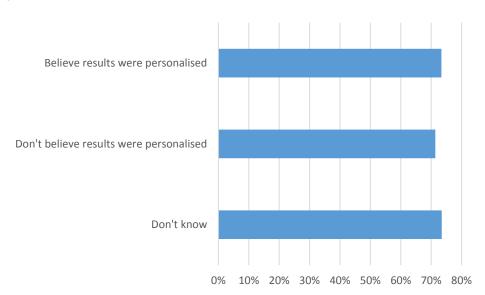


Figure 75: Proportion of participants purchasing products, by whether they believe personalisation had occurred

Note: Question PP9: "For some participants the [insert1 text above] that they were shown had been personalised based on their [insert2 text above]. Were you one of these participants?" N=6.580.

Source: London Economics analysis of online experiment data

However, personalisation did have an impact on respondents' tendency to purchase products that had been personalised to them, as discussed in the following section.

6.2.2. Which products participants chose and why, by treatment, scenario and sociodemographic group

The behavioural experiment did not find any evidence that transparency in regard to personalisation by the website (transparency treatment), nor the personalisation practices themselves (scenarios) had an effect on the probability of participants purchasing products that had been personalised to them (Table 67 and Table 68). However, when looking at both the personalisation scenarios combined with the transparency treatments, the following practices had an impact on the probability of participants purchasing a product that had been personalised to them (that is, personalised based on the scenario the respondent was given in the experiment) in the low transparency treatment (Table 69). When participants experienced targeted advertising combined with personalised ranking of offers they were more likely to purchase a product that been personalised. This effect was observed across all transparency treatments but was statistically significant in the low transparency treatment.

- When participants experienced price discrimination that increased the prices of the personalised products (which was set at 20% in the experiment), they were less likely to purchase a personalised product.
- When price discrimination lead to a decrease in the prices of the personalised products (again set at 20% in the experiment), this resulted in an increase in the proportion of respondents purchasing one of the personalised products

The experiment was designed such that there were three personalised products shown to respondents in a list of eight products in total. In Table 67 and Table 68, the personalised products are labelled 1, 2 and 3.

Across all transparency scenarios including the baseline, product number 1 was selected most often by respondents. Product number 1 was selected 24% of the time across all personalisation scenarios. In many cases product number 1 was positioned first in the list of offered products. The second most popular product was number 3, with 16.6% of respondents selecting this product across all scenarios and treatments. Relatively few participants (between 9.9% and 12.8%) selected product 2, which was usually the most expensive product shown to participants.

Table 67: Product purchased, by scenario

Product label	No personalisatio n	Personalised ranking of offers	Price discrimination	Targeted advertising	Across all scenarios
	%	%	%	%	%
1	22.8	24.5	23.2	25.0	24.2
2	9.9	12.8	11.4	11.2	11.8
3	17.3	16.3	15.5	17.9	16.6
4	9.9	6.0	10.2	7.2	7.8
5	10.0	10.2	9.0	9.2	9.5
6	12.9	7.1	7.9	6.9	7.3
7	12.0	15.8	15.6	15.7	15.7
8	5.2	7.4	7.1	6.9	7.1

Note: This data is aggregated over all three product types (car rental, consumer electronics, and holiday accommodation).

Source: London Economics analysis of online experiment data

A similar pattern is observed when analysing purchasing behaviours across treatments (Table 68). Experiment respondents were most likely to purchase product number 1, which (as previously stated was most often shown at the top of the list), and product number 3.

⁴²⁰ Table 67 and Table 68 show the product purchased by respondents in the first run of the experiment. Participants completed three experiment runs in total.

⁴²¹ In personalised ranking of offers and targeted advertising combined with personalised ranking, the position of product 1,2 and 3 was fixed and these products were always shown first in the list. In the case of price discrimination these products were always shown in the first three of the list but their position varied (within the first three).

The third and seventh products were among the cheaper products. Product order was randomised among participants who began the experiment at different times. However, if a large number of participants began the experiment at the same time (which happened in the case of e.g. the UK), they were shown products in the same order. Therefore, a price effect may explain why products 3 and 7 were chosen with relatively high frequency even in the baseline.

Table 68: Product purchased, by treatment

Product label	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
1	22.8	24.2	22.6	25.8	24.2
2	9.9	12.9	12.7	9.9	11.8
3	17.3	16.8	16.5	16.4	16.6
4	9.9	6.6	8.8	7.9	7.8
5	10.0	8.5	10.3	9.7	9.5
6	12.9	7.4	7.0	7.5	7.3
7	12.0	16.5	15.1	15.6	15.7
8	5.2	7.2%	7.0	7.2	7.1

Note: This data is aggregated over all three product types (car rental, consumer electronics, and holiday accommodation).

Source: London Economics analysis of online experiment data

Table 69 presents the proportion of respondents who purchased one of the personalised products (product number 1, 2 or 3) when the personalisation scenario is analysed in conjunction with the transparency treatment.

All personalisation practices (scenarios) led to an increase in the proportion of respondents who purchased a personalised product compared to the non-personalisation baseline. This increase was statistically significant for three scenarios in the low transparency treatment. 423

In the 'price discrimination' scenario with higher prices, 37% of participants selected personalised products (with 20% higher prices relative to the baseline) compared to 50% of participants in the 'no personalisation' scenario. Conversely, in the 'price discrimination' scenario with lower prices, 66% of participants selected personalised products with 20% lower prices. Finally, 62% of participants in the 'targeted advertising' scenario with personalised offers, selected personalised products.

Table 69: Proportion of participants purchasing products 1, 2 and 3 in the experiment, by scenario and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
No personalisation	50	-	-	-	50
Personalised ranking of offers: based on browser	-	55.4	52.3	47.6	51.5
Personalised ranking of offers: based on previous searches	-	53.2	58.8	54.1	55.5

⁴²³ In the high transparency treatments, participants were also more likely to purchase personalised products relative to the baseline, in the price discrimination scenarios, and when targeted advertising was combined with sorting of search results. However, there was more variance in the high transparency treatments and the difference in proportion was marginally statistically insignificant.

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
Price discrimination: high prices	-	37.1	37.8	41	38.7
Price discrimination: low prices	-	65.6	60.2	63	63
Targeted advertising with random sorting of search results	-	51.6	45.6	51.4	49.5
Targeted advertising with personalised ranking of offers	-	62.5	55.5	57.8	58.4
Total	50	53.9	51.8	52.1	52.6

Note: This table displays the proportion of participants purchasing products across all 3 runs of the experiment **Source: London Economics analysis of online experiment data**

While personalisation practices were observed to impact the probability that a personalised product was selected by participants in the experiment, the practices did not lead a statistical difference in prices paid for the products compared to the baseline of no personalisation (Table 70). This is in line with the findings of the mystery shopping exercise, where personalised ranking of offers was not associated with significantly different prices paid for personalised products (see Section 5.1.4).

Table 70: Average prices paid for top 3 ranked products in the experiment for low transparency treatment, by scenario and products

	Car rentals	TVs	Holiday rentals
	€	€	€
No personalisation	46.1	625.7	718.1
Personalised ranking of offers: based on browser	46.7	656.5	760
Personalised ranking of offers: based on previous searches	47.8	639	724.9
Price discrimination: high prices	47.4	675.6	700.8
Price discrimination: low prices	37.2	588.6	710.9
Targeted advertising with random sorting of search results	45.3	650.2	707.4
Targeted advertising with personalised ranking of offers	43.9	624.8	665.3

Note: This table displays the proportion of participants purchasing products across all 3 runs of the experiment **Source: London Economics analysis of online experiment data**

When asked the reasons why they had purchased a specific product, respondents were most likely to say they thought the price of product was fair, bearing in mind the price they were told they had previously paid in the scenario they were given at the beginning of the experiment (between 43.6% to 49.6% of respondents gave this answer, Table 70).

Almost 50% of participants in the high transparency plus action treatment indicated that they thought the price was fair, compared to 44.5% of participants in the low transparency treatment. This suggests that participants may be more comfortable with personalisation if it is transparently communicated. This finding is explored further in Section 6.3.

The proportion of participants selecting each of the alternative options is fairly similar across treatments, with an exception being the proportion of participants selecting a product because they felt "the good/service matched the criteria I was required to meet". In the baseline 33.1% of respondents selected this option, whereas under personalisation treatments the proportion of respondents selecting this option ranges from 38.0% to 43.0%. This difference however is not statistically significant.

Table 71: Reasons for selecting the product purchased, by treatment

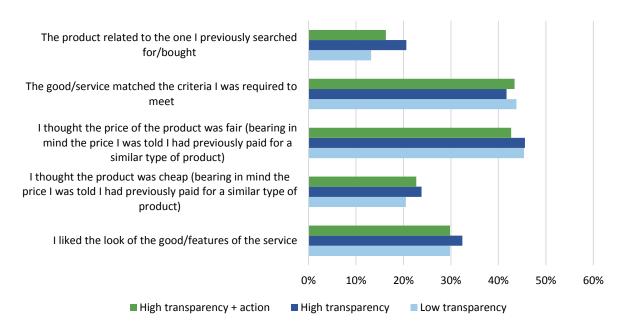
	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
I liked the look of the good/features of the service	31.9	30.7	29.2	30.8	30.3
I thought the product was cheap (bearing in mind the price I was told I had previously paid for a similar type of product)	16.4	22.3	22.0	21.7	21.7
I thought the price of the product was fair (bearing in mind the price I was told I had previously paid for a similar type of product)	43.6	44.5	44.8	49.6	46.2
The good/service matched the criteria I was required to meet	33.1	43.0	38.0	40.6	40.2
The product related to the one I previously searched for/bought	19.4	16.7	20.2	19.8	18.9
N	234	1,465	1,419	1,466	4,584

Note: Question PP8: "What were your reasons behind selecting for purchase the particular product that you did? Please select all that apply." The question allowed multiple responses to be selected, and thus percentages will not sum to 100.

Source: London Economics analysis of online experiment data

The following figures present participants' reasons for purchasing products for each personalisation scenario. Overall, participants' reasoning is consistent across scenarios. The most popular reasons for selecting a product was they thought the product matched the criteria they were required to meet, or they though the price was fair.

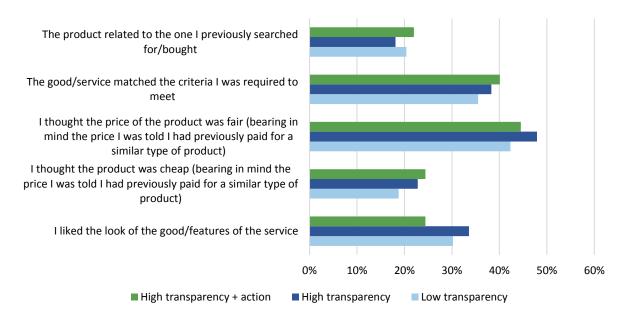
Figure 76: Reasons for selecting the product purchased, personalised ranking of offers scenario



Note: Question PP8: "What were your reasons behind selecting for purchase the particular product that you did? Please select all that apply." The question allowed multiple responses to be selected, and thus percentages will not sum to 100. N=1,465.

Source: London Economics analysis of online experiment data

Figure 77: Reasons for selecting the product purchased, price discrimination scenario



Note: Question PP8: "What were your reasons behind selecting for purchase the particular product that you did? Please select all that apply." The question allowed multiple responses to be selected, and thus percentages will not sum to 100. N=1,419.

Source: London Economics analysis of online experiment data

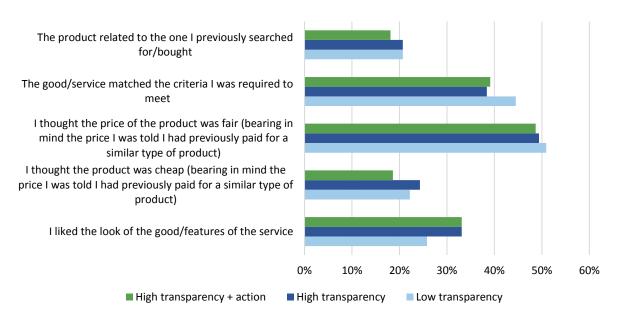


Figure 78: Reasons for selecting the product purchased, targeted advertising scenario

Note: Question PP8: "What were your reasons behind selecting for purchase the particular product that you did? Please select all that apply." The question allowed multiple responses to be selected, and thus percentages will not sum to 100. N=1,466.

Source: London Economics analysis of online experiment data

6.2.3. Whether participants chose to switch platforms and why

Participants in the experiment had the choice once they had reached the confirmation stage of the purchase process to change their mind search again on a different platform.

When the website employed a high level of transparency in regard to personalisation practices and made it easier for participants to clear cookies, participants were less likely to change their mind at the point of purchase and to search again on a different platform. The proportion of respondents who chose to switch platforms was 26.3% in the high transparency + action treatment compared to 33.6% in the low transparency treatment. In the baseline of no personalisation it is $37.5\%^{424}$.

The difference in the proportion of participants selecting to switch platforms is statistically significant in personalised ranking of offers when search results were sorted based on the browser; and in the targeted advertising with personalised ranking of offers. In these two cases, the proportion of respondents who switched platforms was higher in the low transparency treatment where the personalisation practices employed were not communicated to participants.

The result may suggest that when consumers experience and are aware of personalisation, they may want to turn away from the platform. However, consumers may be more reassured if personalisation is communicated transparently and it is made easy for them to limit sellers' ability to personalise by e.g. clearing cookies.

⁴²⁴ When the proportion of respondents clearing cookies is also taken into account, these differences become negligible. That is, the proportion of respondents switching or clearing cookies in the low transparency treatment is 34.4%, in high transparency this proportion is 32.9% and in high transparency plus action it is 33.6%. However, clearing cookies and remaining with the same website is a less overt action than switching to another website altogether.

Table 72: Proportion of participants who chose to switch platforms in the experiment, by scenario and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
No personalisation	37.5	-	-	-	37.5
Personalised ranking of offers: based on browser	-	39.1	28.6	26.5	31.4
Personalised ranking of offers: based on previous searches	-	29.2	34.5	21.9	28.5
Price discrimination: high prices	-	36.1	31.1	30.7	32.7
Price discrimination: low prices	-	31.8	36	22.7	30.1
Targeted advertising with random sorting of search results	-	31.1	35.4	33	33.2
Targeted advertising with personalised ranking of offers	-	34.1	30	22.9	29
Total	37.5	33.6	32.6	26.3	31.2

Note: This table displays the proportion of participants switching platforms across all 3 runs of the experiment **Source: London Economics analysis of online experiment data**

In general, across all products, participants in the low transparency treatments tended to switch platforms more often than participants in the higher transparency treatments. However, the difference was not statistically significant (at 95%) except in the case of TVs.

Table 73: Proportion of participants who chose to switch platforms in the experiment, by product and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Car rentals	34.9	28.7	28.1	21.9	26.7
N	100	595	591	593	1,879
TVs	36.8	37.3	32.8	27.9	32.9
N	123	744	740	743	2,350
Holiday rentals	40.6	34.4	36.6	28.7	33.6
N	123	747	739	742	2,351

Note: This table displays the proportion of participants switching platforms across all 3 runs of the experiment **Source: London Economics analysis of online experiment data**

Participants with relatively little experience in online transactions were statistically significantly less likely to switch platforms in the experiment, which is consistent with lower experience or confidence in using the internet. However, there is no statistically significant difference between high and low transparency treatments.

Table 74: Proportion of participants who chose to switch platforms in the experiment, by socio-demographic group, region and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments	
	%	%	%	%	%	
Country group						
EU15	38.5	34.1	33.1	26.4	31.6	
EU13	32.4	31.1	30.1	25.9	29.2	
Age group						
16-34	44	36	31	27	32	
35-54	39	35	34	25	32	
55-64	24	29	29	27	28	
65+	30	23	34	28	28	
Gender						
Male	40	34	32	26	31	
Female	34	34	33	26	31	
Economic activity						
Active	36.8	32.4	32.8	27	31.1	
Inactive	39.3	36.3	32.3	24.6	31.4	
Educational attain	ment					
Medium/High	35.8	35.1	33.9	27.3	32.3	
Low	46.4	23.5	24.3	20.1	24	
Making ends meet						
Not difficult making ends meet	33.2	34.4	34.2	27.6	32.1	
Difficult making ends meet	43.8	32.6	31.1	25.1	30.3	
Experience with online transactions						
Relatively experienced	38.3	34.8	33	27	32	
Relatively inexperienced	33	22.1	29.4	20.2	24.6	
N	346	2,086	2,070	2,078	6,580	

Note: This table displays the proportion of participants choosing to switch platforms across all 3 runs of the experiment. Participants are coded as finding it difficult to make ends meet if they indicate that they find it 'fairly difficult' or 'very difficult' to make ends meet.

Participants are coded as 'relatively inexperienced' with online transactions if they indicate that they use the internet to buy goods/services online once in the last 12 months, or less frequently.

Source: London Economics analysis of online experiment data

Reasons participants chose to switch platforms

The most common reasons for switching platforms were wanting to find better priced products (selected by approximately 59% of respondents), and wanting a larger variety of products to choose from (approximately 51%), as shown in Figure 79.

For respondents who realised they were experiencing personalisation during the experiment, the most common reason they reported for switching platforms was that they wanted to check if they were getting a good deal (between 23% and 25%), and not that they wanted to switch to another provider to avoid the tactic (between 13% and 15%). This suggests that participants did not object to the personalisation in itself, but rather that personalisation may limit their choices.

I wanted a larger variety of products to choose from I wanted better priced products (bearing in mind the price I was told I had previosuly paid for a similar product) I realised the offers were being personalised based on my personal information and wanted to switch to another provider which may not employ these tactics) I realised the offers were being personalised based on my personal information and wanted to check whether I was getting a good deal None of the above 70% 10% 20% 30% 40% 50% 60% ■ Personalised ranking of offers
■ Price discrimination
■ Targeted advertising
■ No personalisation

Figure 79: Reasons for switching platforms, by scenario

Note: Question PP19: "Why did you choose to search again on a different platform? The question allowed multiple responses to be selected, and thus percentages will not sum to 100. N=1,945.

Source: London Economics analysis of online experiment data

Participants in higher transparency treatments (Figure 80) were slightly more likely to report that they had realised that personalisation had occurred and were switching platforms to make sure they were getting a good deal.

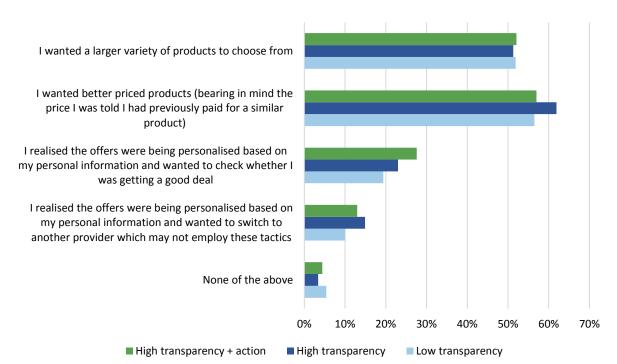


Figure 80: Reasons for switching platforms, by treatment

Note: Question PP19: "Why did you choose to search again on a different platform? The question allowed multiple responses to be selected, and thus percentages will not sum to 100. N=1,945.

Source: London Economics analysis of online experiment data

6.2.4. Whether participants chose to clear cookies and why, by treatment, scenario and socio-demographic group

A very small proportion of respondents chose to clear cookies in the experiment (2.7%). However, this is not distributed evenly across treatments. For those respondents in a low transparency treatment 0.8% chose to clear cookies. In the high transparency treatment this is 0.3%. However, in the high transparency + action treatment, where the 3-click process for clearing cookies is replaced with a single click, the proportion of respondents clearing cookies increases to 7.3%. This pattern is repeated in all sub-scenarios, and the difference between high transparency plus action and other treatments is statistically significant at 95%. This could in part be because having a salient button shown in the experiment simply encourages respondents to click the button.

Table 75: Proportion of participants clearing cookies, by scenario and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
No personalisation	0.5	-	-	-	0.5
Personalised ranking of offers: based on browser	-	0.8	0.9	9.2	3.7
Personalised ranking of offers: based on previous searches	-	0.1	0	9.1	3.1
Price discrimination: high prices	-	0.5	0.7	4.8	2
Price discrimination: low prices	-	1.5	0.1	8.9	3.5
Targeted advertising: random sorting of search results	-	1.1	0.3	4.6	2
Targeted advertising: personalised ranking of offers sorting of search results	-	0.8	0.2	7.4	2.8
Total	0.5	0.8	0.3	7.3	2.7

Note: This table displays the proportion of participants clearing cookies across all 3 runs of the experiment **Source: London Economics analysis of online experiment data**

When comparing across products, participants were (also) more likely to clear cookies if they were in the high transparency treatments compared to the low transparency treatment. This difference is statistically significant (at 99%) and is driven by participants clearing cookies in the higher transparency plus action treatments.

Table 76: Proportion of participants clearing cookies in the experiment, by product and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments
	%	%	%	%	%
Car rentals	0	0.9	0.6	7.5	2.9
N	100	595	591	593	1,879
TVs	1.5	0.7	0	7.5	2.7
N	123	744	740	743	2,350
Holiday rentals	0	0.8	0.4	7	2.6
N	123	747	739	742	2,351

Note: This table displays the proportion of participants clearing cookies across all 3 runs of the experiment **Source: London Economics analysis of online experiment data**

Among potentially vulnerable participants, participants who are 65 years and over, and those who reported they had difficulty meeting ends meet, were significantly more likely (at significance levels of at least 95%) to clear cookies as transparency of communication increased.

Table 77: Proportion of participants who chose to clear cookies in the experiment, by socio-demographic group, region and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Across all treatments	
	%	%	%	%	%	
Country group						
EU15	0.6	1	0.3	7.7	2.9	
EU13	0	0.1	0.4	5.6	1.9	
Age group						
16-34	0	2	1	8	3	
35-54	1	0	0	8	3	
55-64	0	0	0	4	1	
65+	0	0	1	6	3	
Gender						
Male	1	1	0	7	3	
Female	0	1	0	8	3	
Economic activity						
Active	0.7	0.4	0.4	7.5	2.7	
Inactive	0	1.8	0.2	7	2.9	
Educational attainment						
Medium/High	0.6	0.8	0.4	7.6	2.8	
Low	0	0.9	0.1	5.7	2.1	
Making ends meet						
Not difficult making ends meet	0	0.8	0.6	7.3	2.8	
Difficult making ends meet	1.2	0.9	0.1	7.5	2.7	
Experience with online transactions						
Relatively experienced	0.6	0.8	0.4	7.5	2.8	
Relatively inexperienced	0	0.8	0.3	6.3	2.3	
N	346	2,086	2,070	2,078	6,580	

Note: This table displays the high level actions taken across all 3 runs of the experiment. Participants are coded as finding it difficult to make ends meet if they indicate that they find it 'fairly difficult' or 'very difficult' to make ends meet.

Participants are coded as 'relatively inexperienced' with online transactions if they indicate that they use the internet to buy goods/services online once in the last 12 months, or less frequently.

Source: London Economics analysis of online experiment data

Reasons participants chose to clear cookies in the experiment

The most common reasons for clearing cookies were that participants wanted to see what other products were available, a reason which is unrelated to personalisation (relating to consumers' desire for wider choice), and that participants wanted to see if they could get a better priced product, which could again be related to consumers being used to shopping around for the best deal (as shown in Figure 81). That being said, over 25% of respondents stated as one of their reasons for clearing cookies that they realised the offers they were being presented with were being personalised (this proportion is over 30% for those in the personalised ranking of offers scenario).

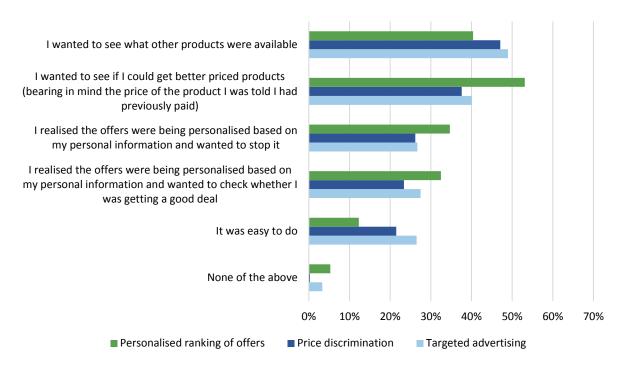


Figure 81: Reasons for clearing cookies, by scenario

Note: Question PP18: "Why did you choose to clear the cookies and search again? The question allowed multiple responses to be selected, and thus percentages will not sum to 100. N=157.

Source: London Economics analysis of online experiment data

Participants' reported reasons for clearing cookies varied, depending on the transparency of communication. For example, participants were more likely to report that they cleared cookies because they realised personalisation had occurred and wanted to stop it in the low transparency treatment, compared to higher transparency treatments. Similarly, participants in the low transparency treatment were, on average, more likely to report that they cleared cookies because they wanted to see if they could get better priced products, or what other products were available.

Overall, the results suggest that even when consumers report being aware of personalisation, they take action to avoid adverse outcomes of personalisation (e.g. limited choice or higher prices), rather than objecting to personalisation itself.

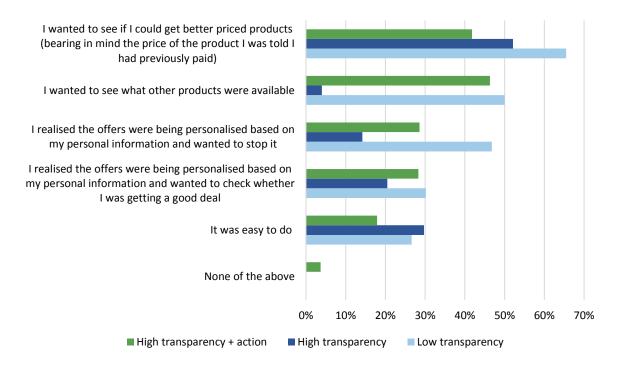


Figure 82: Reasons for clearing cookies, by treatment

Note: Question PP18: "Why did you choose to clear the cookies and search again? The question allowed multiple responses to be selected, and thus percentages will not sum to 100. N=157.

Source: London Economics analysis of online experiment data

6.3. Participants' feelings regarding personalisation practices in real life and how this would impact their behaviour

The behavioural experiment explored participants' feelings about online personalisation practices in the experiment and in real life, and how personalisation would affect their purchasing behaviour and feelings.

The experiment results suggest that experiment participants tended to be focussed on the outcomes of online personalisation i.e. the prices they paid for products, whether they were well-matched to products or the time spent searching. For example, when participants reported that they would continue their experiment purchase in real life, the top-reported reasons (across all personalisation scenarios) were that personalisation allowed participants to more easily choose suitable products, matched products to their needs, reduced search times or could lead to lower prices. When participants reported that they would not proceed with the purchase, or weren't sure, the top-reported reasons were that they thought prices were higher than they would ordinarily be, and that they did not like their data being used to build an online profile. Participants did not seem to be concerned about communication transparency: relatively few participants indicated that they wanted more transparent communication of personalisation as a reason for not proceeding with an online purchase.

6.3.1. Whether participants would proceed with an online purchase if the platforms were personalising: findings from the behavioural experiment

In the experiment, respondents allocated to the price discrimination/personalised pricing scenario were told during the post-experiment questions that price discrimination had occurred on the platform whilst they were searching. For those allocated to the high price

node, they were explicitly told that the prices they were shown were higher than they would have been otherwise due to the tracking of information based upon their previous search and purchase history, and for those allocated to the low price node they were told that the prices they were shown were lower due to personalisation.

Figure 83 presents respondents' feelings towards personalisation. The questions were presented using a 5 point scale where 1 was totally disagree and 5 was totally agree (the figure uses a scale of 0 to 4 for ease of presentation). The results indicate an interesting situation where consumers are willing to continue to use online platforms if they are offered lower prices as a result of these practices, while also being unhappy with the tracking that is involved in personalisation. 'I would be willing to continue shopping on platforms like this but only if I was offered lower prices' was the statement which respondents most agreed with, with an average score of 3.5 across both price discrimination nodes. For those in the high price node, the next statement with the most agreement is 'I would not be willing to continue shopping on platforms like this because my online behaviour is being tracked' (3.1 compared to 2.9 for the low price node), and for those in the lower price node it was 'I consider the practice as acceptable as sometimes I will be offered lower prices and sometimes I will be offered higher prices' (3.2 compared to 2.8 for the high price node).



Figure 83: Feelings about price discrimination, by direction of price discrimination

Note: Question PP16a/b: The prices of some of the products that you were shown on the online platform were [higher/lower] than they would have been otherwise, due to the tracking of information based upon your previous search and purchase history. How do you feel about this? Please select a number on the scale between 1 totally disagree and 5 totally agree for each statement."

Source: London Economics analysis of online experiment data

6.3.2. Whether participants would proceed with their experimental purchase in real life

This section analyses the questions which asked participants in the experiment about their willingness to proceed with the purchases that they made in the experiment, in real life.

As Table 78 below shows, in general scenarios the willingness to proceed with a purchase in real life was very similar across treatments, with approximately 40% of all respondents indicating that they believed they would do so. The only exception was the 'price discrimination' scenario where participants were shown higher prices for personalised products, where willingness to proceed with an online purchase was approximately 35%.

Table 78: Percentage of respondents who are willing to proceed with the purchase in real life, by scenario and treatment

	Baseline	Low transparency	High transparency	High transparency + action	Total
	%	%	%	%	%
No personalisation	40.9				40.9
Personalised ranking of offers: based on browser		40.6	41.7	38.8	40.3
Personalised ranking of offers: based on previous searches		44.5	45.7	45.1	45.1
Price discrimination: high prices		31.2	34.6	40.8	35.5
Price discrimination: low prices		37.0	39.1	37.7	37.9
Targeted advertising: random sorting of search results		47.2	46.3	40.8	44.8
Targeted advertising: personalised ranking of offers sorting of search results		36.2	40.6	38.9	38.6
N	346	2,086	2,070	2,078	6,580

Note: Question PP23: "Do you believe you would proceed with this purchase in real life, bearing in mind the price you were told you had paid for a similar product at the beginning of the exercise?"

Source: London Economics analysis of online experiment data

For those respondents who responded that they would proceed with the purchase in real life, and were allocated to the personalised ranking of offers or price discrimination scenarios, Figure 84 below shows the reasons behind this. The most common responses were related to benefits with respect to product selection ('personalisation allows me to more easily choose products that suit my needs', and 'personalisation shows me more relevant products'), and ease of search ('personalisation reduces the time I need to spend searching for the right product'), with approximately 45% of respondents selecting each of these reasons. Another notable result is the 40% of respondents that selected that personalisation could lead to lower prices as a reason for purchasing in real life (in the price discrimination scenario).

For those participants in targeted advertising (Figure 85), the results were similar, with the most common reasons being 'personalisation allows me to more easily choose products that suit my needs' (47%), and 'personalisation reduces the time I need to spend searching for the right product' (45%).

Across all three practices a common finding is that consumers did not seem to be concerned with the possibility that an e-commerce website could offer a consumer

reductions/promotions as a result of personalisation. Only 20%-24% of participants indicated this reason for proceeding with the purchase. Similarly, only 22% - 27% of participants were incentivised to proceed with a purchase on the basis that personalisation could make searching more enjoyable (22%-27%). The experiment findings are also in line with previous research on the low attention paid to advertisements when searching online, with only 16% of respondents selecting that they liked seeing adverts related to their needs as a reason for proceeding with the purchase (in the targeted advertising scenario).

Figure 84: Reasons for proceeding with purchase in real life, personalised ranking of offers and price discrimination



Note: Question PP24a: "You said in the previous question that you would proceed with this purchase in real life. What is the reason for your response to the question? Please select all that apply." The question allowed multiple responses to be selected, and thus percentages will not sum to 100.

Source: London Economics analysis of online experiment data

Personalisation could lead to lower prices

Personalisation allows e-commerce websites to offer me reductions/promotions

Personalisation makes searching more enjoyable

Personalisation shows me more relevant products

Personalisation reduces the time I need to spend searching for the right product

Personalisation allows me to more easily choose products that suit my needs

0% 5% 10% 15% 20% 25% 30% 35% 40% 45% 50%

Targeted advertising

Figure 85: Reasons for proceeding with purchase in real life, targeted advertising

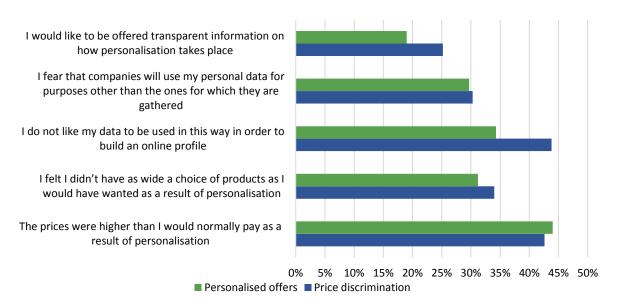
Note: Question PP24b: "You said in the previous question that you would proceed with this purchase in real life. What is the reason for your response to the question? Please select all that apply." The question allowed multiple responses to be selected, and thus percentages will not sum to 100.

Source: London Economics analysis of online experiment data

For those respondents allocated to the price discrimination scenario who indicated that they would not proceed with the purchase in real life, Figure 86 shows that the most common reason selected was that participants do not like their data to be used in this way in order to build an online profile (44%). The next most common response, which was also the most common response for respondents allocated to a personalised ranking of offers scenario, was that they felt the prices were higher than they would normally pay, as a result of the personalisation. This was also the most common reason for those allocated to targeted advertising (Figure 84), with approximately 45% of respondents selecting it. Interestingly, one of the least popular reason across the scenarios⁴²⁵ was that participants would like to be offered transparent information on how personalisation takes place, which when examined in the context of the most popular responses, indicates that consumers are more interested in the end outcome (higher prices, online profiles being built, less choice of products), than how companies communicate transparently the way they are personalising.

⁴²⁵ The least popular reason across treatments was also that participants would like to be offered transparent information on how personalisation takes place. 24% of respondents in the 'low transparency' and 'high transparency plus action' treatment selected this reason.

Figure 86 : Reasons for not proceeding with purchase in real life, personalised ranking of offers and price discrimination



Note: Question PP24c: "You said in the previous question that you would not proceed with this purchase in real life. What is the reason for your response to the question? Please select all that apply." The question allowed multiple responses to be selected, and thus percentages will not sum to 100.

Source: London Economics analysis of online experiment data

I do not like seeing adverts that are targeted specifically to me

I would like to be offered transparent information on how personalisation takes

I fear that companies will use my personal data for purposes other than the ones for which they were gathered

I do not like my data to be used in this way in order to build an online profile

I felt I didn't have as wide a choice of products as I would have wanted as a result of personalisation

The prices were higher than I would normally pay as a result of personalisation

Figure 87: Reasons for not proceeding with purchase in real life, targeted advertising

■ Targeted advertising

Note: Question PP24d: "You said in the previous question that you would not proceed with this purchase in real life. What is the reason for your response to the question? Please select all that apply." The question allowed multiple responses to be selected, and thus percentages will not sum to 100.

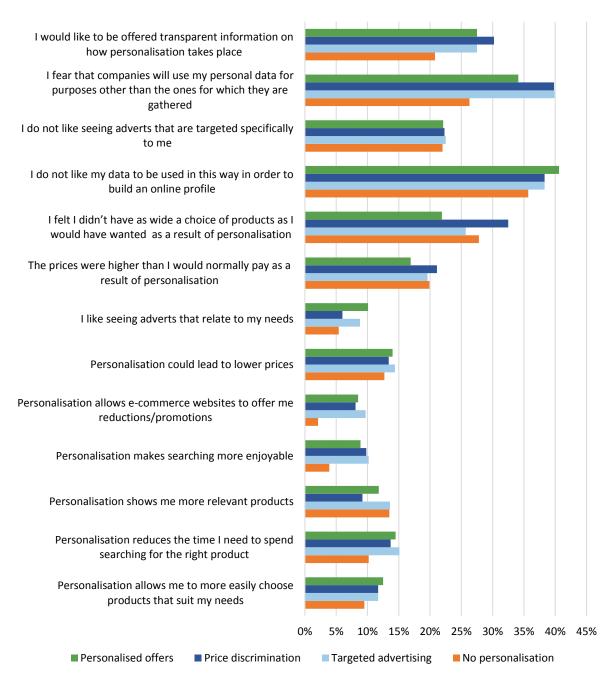
5%

10% 15% 20% 25% 30% 35% 40% 45% 50%

Source: London Economics analysis of online experiment data

Figure 88 shows the reasons given by respondents who answered 'Don't know' about proceeding with the purchase in real life. The responses by these respondents indicate that uncertainty about what their data could be used for puts consumers off purchasing on platforms that use personalisation. The most common reasons were the fear that companies will use data for purposes other than the ones for which they are gathered, and that respondents do not like their data being used to build an online profile about them.

Figure 88 : Reasons for not being sure about proceeding with purchase in real life, all personalisation scenarios



Note: Question PP24e: "You said in the previous question that you did not know whether you would proceed with this purchase in real life. What is the reason for your response to the question? Please select all that apply." The question allowed multiple responses to be selected, and thus percentages will not sum to 100.

Source: London Economics analysis of online experiment data

6.4. Summary of results on the influence of personalised pricing/offers on consumers' decisions and remedies

The box below summarises how the behavioural experiment answers the study's research questions on the influence of personalised pricing/offers on consumers' decisions and remedies.

Box 5: Summary of findings – Influence of personalised pricing/offers on consumers' decisions and remedies

Influence of online personalisation on consumers' decisions

- Participants' personal beliefs about whether they experienced personalisation did not have an effect on their purchasing behaviour in the experiment. Irrespective of whether they thought personalisation was occurring, 72% of participants overall chose to purchase a product in the experiment.
- Personalisation practices and transparency regarding personalisation by the online platform did not have a statistically significant impact on participants' propensity to purchase a product in the experiment.
- However, in three particular scenarios, the type of personalised practice employed had an impact on the probability that a personalised product (usually products based on the shoppers' previous online behaviour and placed prominently in positions 1-3 of all ranked products) was selected by participants. More specifically, in targeted advertising combined with personalised ranking of offers, 62% of participants chose to purchase a personalised product compared to only 50% in the no personalisation baseline scenario. In the price discrimination scenario where participants where shown lower prices, 66% of them chose to purchase a personalised product. In contrast, in the price discrimination scenario where participants where shown higher prices, only 37% of participants (as opposed to 50% in the no personalisation baseline scenario) purchased a personalised product. This was the case in the low transparency treatment only, where there was no salient communication that personalisation was taking place.
- When consumers chose to purchase one of the products that had been personalised to them, based on their previous online behaviour, their main reasons for this purchase were that they thought the price was fair, compared to prices paid previously for similar products, or that the product met their searching criteria.
- Increased transparency by websites that personalisation is occurring may give consumers with less online experience more confidence in making an online purchase. Overall respondents who had less online experience were the least likely to make purchases in the experiment. However, when the website increased its transparency the likelihood that these respondents would make a purchase also increased from 56% in the low transparency treatment to 62.3% in the high transparency + action treatment.
- Overall, 31% of participants chose to switch to another online platform to continue with their purchase during the course of the experiment. The most common reasons for switching were wanting better priced products and a larger variety of products to choose from.
- Increased transparency that personalisation was taking place and simplification of the clearing cookies process lead to a decrease in the proportion of participants choosing to switch platforms at the point of purchase confirmation. The proportion of respondents who chose to switch platforms was 26.3% in the high transparency + action treatment compared to 33.6% in the low transparency treatment.

• Overall, 2.7% of participants chose to clear cookies and search again. The percentage was much higher (7.2%) in the high transparency+action treatment where the option of clearing cookies was offered in a visible one-way easy step.

Participants' feelings regarding personalisation practices in real life and how this would impact their behaviour

- Transparency in communication with regard to how the website was using users' personal data, did not have an impact on participants' willingness to proceed with the purchase in real life. On average across all personalisation scenarios, in the low transparency treatment 39% of respondents stated they would proceed with the purchase compared with 41% in the high transparency treatment and 40% in the high transparency plus action treatment.
- The most common reasons for continuing with a purchase in real life, after the participants had been informed that some form of personalisation was occurring, were allowing the respondent to more easily choose products that suited their needs (between 44% and 55% depending on the personalisation scenario) and that personalisation reduces their search time (between 44% and 45% depending on the scenario).
- The most common reasons for not proceeding with a purchase were that prices may be higher than they normally pay (between 43% and 46% depending on scenario), that their data may be used to build an online profile about them (as high as 44% in the price discrimination scenario) and that the choice of products offered would not be as wide (as high as 35% in the targeted advertising scenario).
- Those participants who were unsure whether they would proceed or not in real life quoted reasons that had to do with not liking their data to be used in order to build an online profile (between 36% and 41%) and fears that their personal data would be used for other purposes than the ones for which they were gathered (between 34% and 40%).

7. Economic effects of online personalisation on consumers and sellers

This chapter presents evidence on the existence of online personalisation practices identified in Chapter 5, and discusses the impacts of online personalisation on the allocation of welfare between sellers and consumers.

The mystery shopping exercise conducted for this study found robust evidence of personalised ranking of offers, but could not detect any systematic evidence of personalised pricing. This finding, based on the mystery shopping data, raises the following question. If prices are not significantly different depending on whether sellers can observe consumers' personal characteristics, then what is the benefit to sellers of personalised ranking of offers?

The findings of the behavioural experiment suggest that sellers may benefit from personalised ranking of offers (even without personalised pricing) because, in certain situations, consumers may be more likely to purchase the personalised products than in a 'no personalisation' situation (6.2.2). The benefit to sellers would therefore be an increase in the number of actual products sold due to the personalisation.

The economic welfare impact of personalisation practices can be both positive and negative from the point of view of consumers. In general, personalisation will benefit consumers who are price-sensitive, who actively shop around and are tech-savvy, or who are able to take steps to protect their personal information. On the other hand personalisation may disadvantage naïve or less engaged consumers or consumers who have a higher willingness to pay.

Personalisation practices may also benefit consumers due to products better matching their personal preferences or due to reduced search costs. However, personalisation may disadvantage consumers if it is used to steer them towards products which may not best match their needs, or which cost the maximum that consumers are willing to pay.

7.1. Possible impacts of online personalisation on welfare allocation between sellers and consumers

The mystery shopping exercise conducted for this study found evidence of widespread personalised ranking of offers in the sample: 61% of the websites personalised the ranking of offers in at least one of the parameters in the analysis (access route to the website, type of browser or device, tracking of online behaviour) – see Section 5.1.1. Therefore, personalised ranking of offers might have widespread use, and the desk research indicates that the use of targeted advertising is pervasive too, and that the targeted advertising market has a sizeable economic value (see Section 2.2).⁴²⁶

What might drive sellers' use of these personalisation practices? Literature suggests that one possible reason is that online sellers might wish to steer certain consumers towards more expensive products. When it comes to market segmentation through personalised pricing (or else price discrimination), this could refer to the situation where online firms are able to adapt their prices according to consumers' willingness to pay. This can result in additional consumers, with a lower willingness to pay also being served. Another reason is that online firms might use personalised ranking of offers and targeted advertising to encourage more consumers to purchase the personalised products that match their needs.

⁴²⁶ Since the mystery shopping exercise did not find robust evidence of personalised pricing, it was not possible to carry out a quantitative assessment of the welfare distribution between sellers and consumers. However, as noted in Section 5.1.3, not detecting personalised pricing as part of this study, taking into account the certain technological limitations, doesn't necessarily mean that this practice does not exist in real life situations.

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The mystery shopping exercise does not find robust evidence of substantial price personalisation or that personalised offers are substantially more or less expensive than non-personalised offers (see Section 5.1.2 - 5.1.4).

However the behavioural experiment does find evidence that in some situations consumers may be more likely to purchase personalised products. Participants in the behavioural experiment who did not receive transparent communication about personalisation were significantly more likely to purchase personalised products when they experienced targeted advertising combined with personalised ranking of offers (see Section 6.2.2).

7.1.1. How could personalised ranking of offers and targeted advertising influence consumers' purchasing decisions?

The results of the behavioural experiment are in line with previous research suggesting that consumers are more likely to purchase top-ranked products (see FCA (2015)⁴²⁷), and also consistent with evidence on the effectiveness of behaviourally targeted advertising. Using data obtained from large advert networks, Beales (2009) estimates that targeted advertising was more effective and cost advertisers 2.68 times the price of traditional advertising. The report by IHS Markit (2017) shows that behaviourally targeted adverts have a click-through rate (the ratio of users who click on a specific link to the number of total users who view an advertisement) 5.3 times higher on average than advertising that does not use behavioural data.

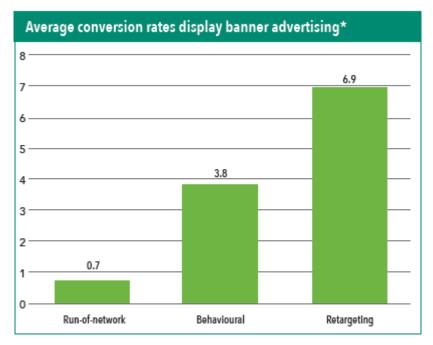
According to the report, data-driven advertising is "500 % more effective than advertising without data, and increases the value of advertising units by 300%"⁴²⁹. The figure below displays the impact on conversion rates (i.e. the number of customers who have completed a transaction divided by the total number of website visitors) of behavioural advertising and retargeting, compared to standard "run-of-network advertising" (online advertising applied to a wide collection of websites, without the ability to choose specific sites), as reported by the IHS Markit industry survey.

⁴²⁷ FCA (2015), High-Cost Short-Term Credit Price Comparison Websites, prepared by London Economics and YouGov

⁴²⁸ Beales, H. (2009). "Value of behavioural advertising." Available <u>here.</u>

⁴²⁹ IHS Markit (2017)³³

Figure 89: Effect of behavioural advertising and retargeting on advert conversion rates



Source: IHS Markit industry survey, 2017. Data refers to advertising campaigns in the EU-28.

Using behavioural data seems to be particularly valuable in deepening consumers' interest in a product: when behavioural data is used to specifically target people who have paid attention to a product previously, the click-through rate is 10.8 times higher.⁴³⁰ There are a number of reasons that targeted advertising may be effective. One reason is that targeted advertising matches consumers to sellers. This benefit of online personalisation was observed in the consumer survey (Section 4.2.1) as well as in the behavioural experiment (Sections 4.7 and 6.3).

Another reason that behaviourally targeted advertising may be effective is that targeted advertising may affect consumers' perception of themselves, leading them to change their behaviour to match the behaviour suggested by the advertisement. (Bagwell, 2005) Summers, Smith and Reczek (2016) look in this context at behaviourally targeted advertisements. They find evidence which suggests that when consumers recognise that the advertiser has made an inference about their identity in order to tailor the advert to them, "the ad itself functions as an implied social label."⁴³¹ Behaviourally targeted advertisements, the study argues, lead consumers to adjust their self-perceptions to match the label. According to the authors, these unique psychological effects can make behaviourally targeted advertisements more effective than traditional adverts that rely on demographic targeting. This line of reasoning draws on literature that builds on the view of advertising as "persuasive" rather than "informative". ⁴³² According to the former view, the main effect of advertising is that it influences consumers' tastes, creating spurious product differentiation and brand loyalty. The "persuasive" view of advertising suggests that it brings no "real" benefit to consumers.

The behavioural experiment does find evidence suggesting that participants who correctly identified personalised ranking of *offers* were more likely to purchase personalised products if they faced targeted advertising and personalised ranking of offers. 82% of participants who correctly identified personalised ranking of offers and also faced targeted advertising

⁴³¹ Summers, C., Smith, R. and Reczek, R. (2016). An Audience of One: Behaviorally Targeted Ads as Implied Social Labels. Journal of Consumer Research, Volume 43, Issue 1, 1 June 2016, Pages 156–178. Available here.

⁴³⁰ IHS Markit (2017)³³

⁴³² Bagwell, K. (2005). "The Economic Analysis of Advertising." Available here.

in the low transparency treatment purchased personalised products, compared to 61% who did not correctly identify personalised ranking of offers. The effect was statistically significant at 95%. This effect may be linked to the 'persuasive' view of advertising discussed above, which argues that consumers may alter their behaviour to match their online 'profile'.

However, online personalisation may also benefit consumers by matching them to products that better suit their interests, the so-called 'informative' view of advertising. ⁴³³ The "informative" view of advertising suggests that the value of advertising is in reducing search costs and improving matches while treating consumers' preferences as given. Indeed, personalisation in general may increase demand and consumer welfare by reducing search costs and improving the quality of matches for consumers.

The existing evidence regarding consumer impacts of online personalisation is discussed below.

7.1.2. Existing evidence about consumer impacts of online personalisation

As previously stated, the existing evidence suggests, broadly, that online personalisation can benefit consumers if it matches them to lower prices, to the products that best suit their needs, or if it reduces their search costs. However, personalisation can negatively affect consumers if it is used to steer them towards the most expensive products that they are willing to pay. In turn, personalisation may benefit consumers who actively shop around, but can harm consumers who are not able or willing to search, or who have a high willingness-to-pay.

The consumer survey suggests that consumers believe that improved price and product matches may indeed be a benefit of online personalisation. For example, when participants were asked what would make them more likely to purchase a product, the top reported answer was 'seeing products at the best available price', followed by 'the products matching my requirements or interests' (see Figure 90 overleaf). Participants also indicated that one of their top perceived benefits of personalisation was that they would see the products that they might be more interested in(see Section 4.2.1). This indicates that, if personalisation works like this, it may be able to increase consumer demand by showing them products that better suit their needs.

⁴³³ Bagwell, K. (2005). "The Economic Analysis of Advertising." Available <u>here</u>.

Figure 90: What would make participants more likely to purchase a product in the future



Note: QP1. Thinking about your recent purchases/shopping online, what would make you more likely to purchase a product in the future? Select all that apply. The question allowed multiple responses to be selected, and thus percentages will not sum to 100. N=6,395.

Source: London Economics analysis of online experiment data

This finding is in line with existing theoretical literature which argues that online personalisation may increase social welfare through better matches. For example, Chen and Stallaert (2014) build a theoretical model that studies payoffs of advertising publishers and advertisers, comparing targeted and traditional advertising. They argue that targeted adverts are associated with higher combined payoffs (and therefore social welfare) because users are assigned to advertisers that value them the most. 434

However, other research argues that targeted advertising benefits consumers only if certain types of information are exchanged. Marotta et al. (2015) find that consumer welfare increases if information on consumers' preferences for specific products is exchanged rather than information on differences in consumers' purchasing power. In other words, targeted advertising helps consumers if it matches them to the product they like the most, but not if it matches them to the most expensive product they are willing to purchase. 435

This is in line with the findings of the behavioural experiment, where participants' main reasons for not proceeding with experimental purchases in real life were linked to paying higher-than-normal prices and to worries about their data being used in order to build an online profile (see Section 6.3.2). This is equally in line with the consumer survey, where respondents' major concerns regarding online personalisation practices were concerns about data being used to build an online profile and data being used for other purposes (Section 4.3.1). Therefore, trusting that the online retailer safeguards consumers' personal data is a key issue for consumers to feel safe in order to proceed to purchasing products online (Figure 90 above).

When it comes to prices charged to consumers, the literature on price discrimination demonstrates that the net effect of price discrimination on consumer, seller, and total surplus largely depends on specific market circumstances, including for example the intensity of competition and type of price discrimination available to producers. This is examined in the section that follows.

⁴³⁴ Chen J, and Stallaert, J. (2014). "An economic analysis of online advertising using behavioural targeting." Available here.

 $^{^{435}}$ Marotta et $\overline{\text{al.}}$ (2015). "Who benefits from Targeted Advertising?". Available <u>here</u>.

7.1.3. Can competitive pressures help consumers to retain consumer surplus?

In general, the literature argues that competitive pressures can limit sellers' ability to extract surplus from economic transactions. For example, in the case of a monopoly market where the monopolist can perfectly price discriminate, each customer pays as much as they value the product, and all surplus value is thus extracted by the producer. While this is an extreme case, price discrimination generally transfers some economic value from consumers to sellers.

The extent to which sellers are able to extract more economic value depends on their ability to segment the market into smaller groups of consumers with different characteristics. The UK's (former) Office for Fair Trading (2013), for example, argues that in a market with weak competition, consumer surplus will decrease if firms are able to observe more detailed consumer characteristics and thus segment consumers into smaller groups. As third-degree price discrimination tends towards first-degree discrimination, the dominant seller can extract a greater share of the total surplus. ⁴³⁶

Applied to e-commerce, economic theory would imply that in markets with weak competitive pressures personalised pricing leads to a greater transfer of surplus from consumers to sellers. For example, for sellers, personalisation may be able to influence the price that consumers pay for a product – either because consumers click on targeted advertising for a product, or are steered towards more expensive products, or because consumers pay different prices for the same product (price personalisation). Personalisation enables sellers to determine the maximum that consumers are willing to pay, thereby extracting the maximum possible surplus from each transaction.

If firms personalise towards consumers with a higher willingness to pay, rather than seeking to capture additional consumers from their competitors, then personalisation will have a negative effect on consumer welfare.⁴³⁷

The OECD (2016) further notes that consumers are likely to be harmed if firms engage in "exploitative discrimination". That is, price discrimination schemes that aim to raise markups and increase market power. Such schemes can include, for example, steps to distinguish between sophisticated and naïve customers or other ways to make use of customers' lack of information or behavioural biases.

Consumers are also likely to be harmed by "exclusionary price discrimination", a practice in which firms use price discrimination to exclude a rival firm. Examples include steps to prevent arbitrage, predatory pricing or fidelity and bundled discounts. Firms can use price discrimination in predatory behaviour by e.g. charging lower prices to key customers of a competitor firm. Firms can also provide discounts, or rebates, to loyal customers, which can be used to reward loyal customers or penalise disloyal customers. Exclusionary price discrimination weakens competition, suppressing output, increasing firm mark-ups and reducing consumer and total surplus.⁴³⁸

Oxera (2017) also points out that there may be distributional implications of price discrimination: firms may price discriminate in favour of customers who actively employ personal privacy measures, and against customers who do not. 439 This is in line with the stakeholders' survey (see Section 4.3.2), which suggests that personalisation may affect some socio-demographic groups more than others. In the stakeholder survey 4 out of 16 (25%) CPA respondents reported that personalised pricing/offers could have a negative impact on certain types of consumers.

Consumers may still be able to retain surplus even if sellers personalise prices. If many sellers are able to personalise prices to individuals and small groups, competitive pressures

 $^{^{\}rm 436}$ Office of Fair Trading (2013). "The economics of online personalised pricing".

⁴³⁷ Office of Fair Trading (2013). "The economics of online personalised pricing".

⁴³⁸ OECD (2016). "Price Discrimination: Background Note by the Secretariat."

⁴³⁹ Oxera (2017). When algorithms set prices: winners and losers. Discussion paper.

protect the consumers' interests and consumers are able to retain a larger share of surplus value. In a market with stronger competitive pressures, more effective segmentation of customers increases both total surplus and consumer surplus. (Office for Fair Trading, 2013). However, the important assumption is that *all* sellers are able to segment customers more effectively. In other words, as argued by the OECD (2016, p. 35), "it is best for consumers if all competitors have access to information on their willingness to pay, rather than one firm having exclusive access."

The US President's Council of Economic Advisors (2015) suggest that even "if a company does succeed in charging personalised prices, it must be careful not to alienate customers who may view this pricing tactic as inherently unfair."⁴⁴⁰ An important restraint on price personalisation is consumers' distaste of practices that they feel are unfair. A clear example is Amazon's famous experiment with price personalisation, which led to strong consumer backlash.⁴⁴¹ Richards et al. (2015) argue that consumer perceptions of price fairness are key to the sustainability of any discriminatory pricing regime. According to their experimental data, consumers perceive differential pricing more favourably if they are allowed to participate in the price-formation process by negotiating the price they pay.⁴⁴²

In addition to resenting perceived unfairness, consumers could express concern over privacy intrusions. Gardete and Bart (2017) argue that often "less is more" in online personalisation techniques because consumers might perceive highly personalised content as "manipulative" and less trustworthy. In follow-up questions after completing the behavioural experiment, participants indicated that a major concern with online personalisation was that their data would be used to build an online profile (see Section 6.3.1)

Acquisti and Varian (2005) also stress consumers' power in voicing displeasure for discriminatory or intrusive pricing policies, emphasising mechanisms consumers could use to defend against online price personalisation: "No one is forced to join a loyalty program. It is relatively easy to set one's browser to reject cookies or to erase them after a session is over. Consumers can use a variety of credit cards or more exotic anonymous payment technologies to make purchases anonymous or difficult to trace."444 Assuming consumers' power to protect their privacy, they predict that firms might not find it optimal to personalise prices based on collected personal data. Since each customer can hide their personal data, the firm must offer them some benefit to reveal that information. This additional cost for the firm, Acquisti and Varian argue, is likely to offset the benefits of the collected personal information for the firm.

However, it seems unreasonable to assume that consumers have such control over their privacy. The argument ignores the fact that it is costly (at least in time and effort) for online buyers to employ elaborate techniques to hide their online identity and – more importantly – the argument assumes that consumers are fully informed how their personal data is being collected and used and the ways to prevent this. The behavioural experiment suggests that consumers have limited ability to correctly identify online personalisation. Less than 50% of experiment participants identified personalisation, across all personalisation types and communication transparency treatments (see Section 4.1.2). In addition, some targeted advertising can take the form of 'native advertising' i.e. advertising that matches the 'look and feel' of the content and platform it's on e.g. an advertisement in a news article that has the format and presentation of the article the advertisement is embedded in. A recent study of US trust in media found that 77% of respondents did not

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https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/docs/Big_Data_Report_Nonembargo_v2.pdf

⁴⁴¹ Puget Sound Business Journal (2000). Bezos calls Amazon experiment 'a mistake'

⁴⁴² Richards T. J., Liaukonyte, J., Streletskaya, N. (2015) "Personalized Pricing and Price Fairness". Available <u>here</u>.

⁴⁴³ Gardete, P. and Bart, Y. Tailored Cheap Talk. Working Paper No. 3400. Available here.

⁴⁴⁴ Acquisti, A. and Varian, H. (2005). "Conditioning Prices on Purchase History". Available <u>here</u>.

identify native advertising as advertising, and 54% felt they had been deceived by native advertising.⁴⁴⁵

In addition, the argument assumes that consumers take action to protect their data, which may not be the case in reality. For example, although the consumer survey and behavioural experiment found that consumers are concerned about the impact of personalisation on their data privacy (see Section 4.3.1), the data protection authorities in the stakeholders' survey reported that consumers rarely complained about data protection issues.

7.1.4. Online personalisation impacts on innovation and the broader society

Online personalisation may have wider impacts on markets, sellers and consumers, beyond direct effects such as the impact on whether a transaction takes place or the allocation of welfare between sellers and consumers.

For example, economic theory suggests that the ability to price discriminate can intensify competition between firms. Price discrimination allows firms to charge the consumers who have lower willingness to pay a lower price, "thus allowing them to compete more intensely for each other's customers, without affecting the price they charge other customers." (Office of Fair Trading, 2013, p. 25)⁴⁴⁶ Increased competition, in turn, leads to lower prices and higher output, increasing consumer surplus.

Moreover, in a dynamic setting, price discrimination can create incentives for actions such as investment or innovation that can also ultimately benefit consumers. This is because firms have stronger incentives to innovate if they are able to appropriate a larger share of the social surplus generated by the innovation. By allowing firms to seize a greater share of surplus value, price discrimination can lead to more investment and innovation. 447 (OECD, 2016, p. 10). 448

On the other hand, online personalisation can limit the range of products available to consumers, make them pay higher prices, reduce informed consumer choice and the functioning of competition in markets, as well as raise barriers to competition and innovation.

For example, advertising products that consumers are mostly interested in, based on their past preferences, could be seen as inducing conservatism in consumer preferences and stifling innovation. Such targeting may prevent consumers from being exposed to new information and thus from developing modes of thought and action unlike those with which they are already familiar. In line with this, to some extent personalisation might potentially reduce overall consumption. Targeting consumers who recently purchased a certain product with repetitive ads for similar products might crowd out other ads, which could have potentially generated sales in other market sectors. In this context, approximately half of consumer survey respondents who reported a bad experience with one or more of the 3 online personalisation practices indicated that they were offered products that they were no longer interested in (Section 4.4.1). In addition, the behavioural experiment showed that when respondents did not want to proceed with an online purchase, one major reason was they felt that they didn't have as wide a choice of products as they would have wanted as a result of personalisation.

In general, therefore, economic theory predicts that online personalisation may benefit consumers in certain circumstances, and harm them in others. By ensuring more

⁴⁴⁵ https://contently.com/strategist/2016/12/08/native-advertising-study/

⁴⁴⁶ Office of Fair Trading (2013). "The economics of online personalised pricing". Available here.

⁴⁴⁷ But need not, for example when the generated incentives are to rent-seek through lobbying (OECD, 2016, p. 14).

⁴⁴⁸ OECD (2016). "Price Discrimination: Background Note by the Secretariat." Available <u>here</u>.

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consumers face prices at which they can purchase, personalisation can increase output and lead to greater consumer surplus (Office of Fair Trading, 2013, p. 24).⁴⁴⁹

However, price discrimination may result in adverse impacts for low-income consumers. For example, lower-revenue consumers may be charged more if they are perceived as more likely to default on a loan or to dent a rental car. Price discrimination can be linked to low-income consumers' inability to access conventional credit, leading to their needing to rely on high-cost short-term credit (Social Market Foundation, 2018⁴⁵⁰).

As the OECD (2016, p. 9)⁴⁵¹ notes, while the "use of the word "discrimination" may create an assumption of unfairness and scepticism over the likely benefits of firms charging different prices for similar products, ... there is nothing intrinsically unfair about price discrimination; it can mean that more consumers are served and that those on lower incomes pay lower prices."⁴⁵² On the other hand, personalisation may lead to consumer harm if personal data is exploited to manipulate consumer weaknesses to increase sales or increase prices. In addition, market failures may result from restriction of consumer choice or reduced competition.

⁴⁴⁹ Office of Fair Trading (2013). "The economics of online personalised pricing". Available <u>here</u>

⁴⁵⁰ Social Market Foundation (2018), available here

 $^{^{451}\,\}text{OECD}$ (2016). "Price Discrimination: Background Note by the Secretariat." Available here.

⁴⁵² OECD (2016). "Price Discrimination: Background Note by the Secretariat." Available <u>here</u>.

8. Conclusions and policy approaches

This final chapter of the report presents the key conclusions of the study and puts forward suggested policy approaches based on these conclusions. The chapter is structured as follows:

- 1. Key findings relating to:
 - A. The nature and prevalence of online personalised practices
 - B. Consumers' awareness and perception of online personalised practices and problems experienced
 - C. Assessment of whether businesses are transparent and comply with the existing regulatory framework
 - D. Economic effects of online personalisation on consumers and sellers
- 2. Policy approaches

8.1. Key findings of the study

8.1.1. A) The nature and prevalence of online personalised practices

The study used a number of research tools to study the nature and prevalence of online personalisation. The primary research method was a mystery shopping exercise, carried out in 8 Member States and in four market sectors⁴⁵³, used to investigate the prevalence of online personalised ranking of offers (changing the order of search results to highlight specific goods and services) and online personalised pricing (or else price discrimination, where different prices can be charged to shoppers for the same products) in online markets. In total, 160 e-commerce websites were visited by mystery shoppers. Desk research, a consumer survey in the EU28 plus Norway and Iceland, as well as stakeholder consultations complemented the mystery shopping exercise⁴⁵⁴.

The key findings relating to the nature and prevalence of online personalised ranking of offers and personalised pricing, as well as of targeted advertising, are as follows.

• Evidence of personalised ranking of offers

The mystery shopping exercise found evidence of websites changing the order of search results when different consumers search for the same products online. The data suggests that 'personalised ranking of offers' takes place based on information about shoppers' past online behaviour (such as history of visits/clicks on ads based on cookies, etc.), as well as on information about the shoppers' access route to the website (via a search engine, a price comparison website (PCW), or based on the type of browser or device used). These findings are broadly in line with the results of the literature review and stakeholder survey. The available empirical evidence from the literature points to a high incidence of online personalisation when it comes to altering the ranking of products

⁴⁵³ The countries covered were: 1) Czech Republic, 2) France, 3) Germany, 4) Poland, 5) Romania, 6) Spain, 7) Sweden and 8) the UK. The markets covered were: 1) TVs, 2) sport shoes, 3) hotels rooms, and 4) airline tickets (not websites of airline companies as such but instead websites of platforms selling air tickets). For more information on the methodology of the mystery shopping, see Annex A1.6Error! Reference source not found..

The study included also a behavioural experiment which was specifically designed to measure consumers' awareness of personalised practices and their subsequent decision making when online traders communicate personalisation more transparently.

consumers see when searching online⁴⁵⁵. In certain cases, personalised ranking of offers has been found to relate to the device used to access the website, the geographical location of the user, or being logged-in to an account or not⁴⁵⁶. A number of stakeholders *who responded to the survey* believed that some or most websites use personalised offers (36%). Nonetheless, more than half (15 out of 28) of respondents reported to not know of the incidence of such practices in online markets.

Key findings relating to the incidence of personalised ranking of offers include:

- 1. Over three fifths of the 160 e-commerce websites (61%) visited for this study, were found to practice personalised ranking of offers⁴⁵⁷ in at least one mystery shopping scenario⁴⁵⁸, either through search engines or PCWs or different browsers or a mobile device or based on the shoppers' past online behaviour. This suggests that e-commerce websites can track their users in different ways and that, while relatively few websites may use one particular technique, relatively more websites use some combination of the above mentioned parameters to personalise the ranking of offers for online shoppers.
- 2. Access through a PCW or a mobile device had the strongest impact on the ranking of offers, as opposed to using a different browser or accessing an e-commerce website via a search engine. Moreover, of those websites visited by online shoppers, 54% ranked offers based on at least one of the four types of access to a website, while 44% ranked offers using data collected about the shopper's past online behaviour.
- 3. Websites offering airline tickets or hotel offers were found to practise personalised ranking of offers more frequently than websites offering shoes or TVs. The share of websites practising personalised ranking of offers was 92% for the airline ticket websites, 76% for hotel room websites , 41% for the websites selling sports shoes, and 36% for the websites selling TVs. Websites in Germany and the Czech Republic were found to have the least number of websites undertaking offer personalisation, with 42% and 47% of websites, respectively, altering the ranking of offers in at least one of the four mystery shopping scenarios. By contrast, in Sweden and Poland, the number of websites found to undertake personalised ranking of offers was 75% and 79% respectively.
- 4. Across the EU28, approximately one in two respondents (53%) in the consumer survey reported that, according to their perception, nearly all or most websites use personalised ranking of offers.
- 5. The research method applied in the mystery shopping did not find systematic price differences related to personalised ranking of offers in the four product markets, in case of different top ranked products shown to shoppers on the same website. Some statistically significant but rather small results were found at the level of individual product categories.

Both whether the same five products were listed and whether they were in different order.

⁴⁵⁵ For example, Hannak et al. (2014) found that more than half of the US travel and retail e-commerce websites in the sample were shown to practise some form of online personalisation and some of these websites altered more than half of all search results (personalised ranking of offers).

⁴⁵⁶ (Mikians et al, 2012, Hannak et al, 2015)

⁴⁵⁸ The mystery shopping exercise encompassed 4 scenarios, simulating: a) accessing the e-commerce website via a search engine (e.g. Google), b) accessing the e-commerce website via a price comparison tool (PCW), c) accessing the e-commerce website via a different browser, d) accessing the e-commerce website via a mobile device (as opposed to a desktop). For each website visit, these scenarios were carried out by a shopper in a single sequence (although in a different order), whilst at roughly the same time a researcher carried out an anonymised 'control shop' to the same website (no personalisation scenario), in which consumers' characteristics were hidden (as opposed to the shops by the mystery shoppers). For more information on the methodology of the mystery shopping, see Annex A1.6.

• Evidence of personalised pricing

The research method applied in the mystery shopping did not find evidence of consistent and systematic personalised pricing across the 8 EU Member States and 4 markets covered. Across the four product markets assessed, price differences between personalisation and 'no personalisation' scenarios⁴⁵⁹ were observed in only 6% of matched identical product pairs. Even when price differences were observed, the differences were small, with the median difference being less than 1.6%. Furthermore, prices were not systematically higher or lower in the 'personalisation' scenarios compared to the 'no personalisation' scenario i.e. the net average price difference was not statistically significantly different from zero.

Among the websites visited by mystery shoppers where price differences were observed between 'personalisation' and 'no personalisation' scenarios:

- 1. Airline and hotel booking websites showed relatively higher evidence of price personalisation compared to websites selling TVs and shoes: of the 34 websites showing price personalisation, 19 were for airline tickets, 9 for hotel rooms, 4 for shoes and 2 were for TVs.
- 2. When looking at the specific personalisation scenarios in the mystery shopping, accessing the e-commerce website via a price comparison website (PCW) had the highest impact on the prices observed in the four product markets assessed. In some countries, access to the website through a PCW was linked with a price difference of up to 3% on average compared to direct URL access or access through a search engine.
- 3. In the sample, smaller websites appeared to personalise prices on average more than larger websites. One reason for this may be that larger websites may be more likely to be scrutinised for evidence of price personalisation, and therefore larger websites may have a further disincentive to personalise prices. Smaller websites are more sensitive to small traffic increases compared to larger websites, and therefore mystery shoppers were more likely to observe price differences for identical products there. The fact that the mystery shopping exercise found that small websites personalise prices more than larger websites was especially so in the services sectors (hotels and airlines) where dynamic pricing is more prevalent.
- 4. However, across the EU28, almost three in ten respondents (28%) in the consumer survey reported that, according to their perception, nearly all or most websites use online personalised pricing.

The lack of evidence from the mystery shopping data of systematic personalised pricing is broadly consistent with the existing empirical literature on price personalisation, which doesn't find robust evidence of online price personalisation. With a few exceptions, 460 the evidence in the literature for online price discrimination is scant and relates to a limited number of websites.

The results of the mystery shopping are also in line with the findings from the stakeholder survey conducted for this study, which indicated that the use of personalised pricing is not widespread. Whereas 5 out of 30 (17%) stakeholders believed that "some" websites use personalised pricing, 8 (27%) stakeholders mentioned that very few or no websites use personalised pricing. The majority of respondents (53%) were not aware if such practices are employed by online firms, which could also mean that personalised pricing is a practice which is particularly difficult for consumers to become aware and then detect.

⁴⁵⁹ In the latter, shoppers characteristics (either past online behaviour or access route to the website were not observable by e-commerce websites).

For example, a study suggested that accessing a site via a PWC leads to lower prices (Mikians et al., 2012). There is also some evidence for personalised pricing linked to the device (mobile or desktop) used to access the website, the browser used, the geographical location of the user, being logged-in to an account or not, or previous search behaviour (e.g. searching for luxury products) / other personal characteristics. However, in most of the cases, the evidence is limited in magnitude and accounts for specific websites only.

One reason for the low prevalence of personalised pricing identified in the data for this study may be explained by the controversial nature of the practice: if exposed, a seller that is using online personalised pricing could suffer reputation damage as consumers may not respond positively to personalised pricing. However, the lack of evidence of systematic personalised pricing based on the mystery shopping data should be interpreted with care and it cannot be deduced that online retailers do not use such a practice to charge different shoppers different prices for the same product. There are a number of factors that may explain the lack of evidence of online personalised pricing. For example, it is difficult to detect this practice, as online firms may employ any of the latest sophisticated algorithms or personalisation tools (such as for example digital fingerprinting) which research tools or methodologies cannot easily detect. It should also be noted that the mystery shopping results are based on a (non-random) sample of 160 websites across 4 product categories and 8 EU Member States and may not be representative for the EU e-commerce market as a whole⁴⁶¹.

• Evidence of targeted advertising

The findings from the literature review, consumer survey and stakeholder survey all suggest that targeted advertising in its various forms is the most widespread online personalisation practice.

- 1. Across the EU28, more than two thirds (71%) of respondents in the consumer survey reported that in their experience nearly all or most websites use online targeted advertising.
- 2. In total, 15 out of 28 (54%) stakeholders reported that targeted adverts in their various forms are in their opinion used by "most websites" or "nearly all websites". These findings align with Eurostat statistics from 2016 which show that 78% of all EU businesses using internet adverts have adopted "contextual advertising" 462.
- Type of personal data collected and the techniques used to collect consumers' personal data and segment consumers in online markets

The literature, as well as the stakeholders' and business operators' surveys conducted for this study, suggest that there are a number of different technological means for data collection that can be used in online personalisation.

- 1. Personal data can be volunteered or 'surrendered' by online users themselves (e.g. when creating accounts online or interacting on social media), observed (e.g. when browsing activity is tracked using for example cookies) or inferred (e.g. by combining and analysing data obtained from different sources, often from data brokers, in order to create consumer profiles).
- 2. Online firms can use various tracking methods to follow consumers across different platforms, websites and devices. The use of cookies is the most traditional tracking method, but a plethora of more advanced tracking methods is available. These include digital fingerprinting and web beacons, which the consumer cannot prevent or stop, unless possibly if possessing a high level of IT skills.
- 3. The evidence shows that the more advanced tools needed to prevent the latest sophisticated tracking methods, such as VPNs or the TOR browser, are rarely used by online shoppers. In the consumer survey for this study, 60% of EU28 respondents either never used these tools or didn't know about them, whilst most others use these tools only sometimes or rarely.

⁴⁶² A type of targeted internet advertising that uses technologies embedded in websites and apps that choose ads based on the content of the web pages internet surfers view.

⁴⁶¹ Annex A1.6 summarises the methodology underlying the mystery shopping data collection exercise and how the specific websites included in the mystery shopping where selected.

4. Moreover, e-commerce websites that want to personalise results do not always collect and subsequently process consumer data/profiles themselves; instead they often use specialised companies' personalisation or analytics software or services. The so-called 'data value chain' contains a variety of actors involved in collecting and transmitting users' data. The literature review showed that the marketing data and advertising industry is among the largest sectors in this ecosystem, which encompasses various actors, such as marketing agencies, data brokers, online advertisers, and e-commerce firms. Online platforms (including online marketplaces such as Amazon and social media like Facebook) also play an increasingly important role in the data value chain as intermediaries. For example, they may not only collect personal data to better personalise their content for users, but also allow businesses to better target their products and services on the platform itself, based on users' data. In addition, there exist specialised B2B data platforms on which various actors can have access to high quality (personal) data and may obtain/transmit this data.

The evidence from the literature and stakeholder survey shows that online firms collect many types of personal data, including socio-demographic data (age, gender, etc.), behavioural data (history of website visits, clicks on ads etc.), technical data (IP address, type of browser etc.), and this may include some potentially sensitive data (health, sexual orientation, religion etc.). Although such personal data is often transmitted in 'anonymised' or 'pseudonymised' form, in practice this does not exclude the possibility of individuals being identified, notably because different data sources and types can be easily combined to enable targeting at individual level. Pseudonymisation can be reversed when combined with other data. Moreover, companies often claim to use anonymisation while in reality, they are applying pseudonymisation. This means the distinction between non-personal and personal data in (micro) targeting practices of online advertising, marketing and other content is often blurred.

Published literature suggests that online business operators can use the described tracking methods and the collected data to target individual consumers or certain groups of consumers differently, for example segmenting users based on their willingness to pay. Specialised data analytics companies and data brokers offer personalisation software or data analytics services to e-commerce companies for the optimisation of their marketing and pricing strategy. Pricing algorithms can be used for both price discrimination, as well as for dynamic pricing. Market segmentation through price discrimination could theoretically benefit consumers: price discrimination could lead for example to lower prices for consumers with a lower willingness-to-pay. However, this is not always guaranteed and it could be that, in certain cases, vulnerable consumers may be discriminated because of sensitive personal characteristics or that low revenue consumers may be charged more for a service if they are perceived more likely to for example default on a loan.

To conclude this subsection, it should be noted that the number of online personalisation methods available to e-commerce firms is only expected to expand. A clear majority of business operators consulted for this study supported that emerging technologies such as Artificial Intelligence, in combination with data analytics/machine learning and the Internet of Things, will expand the options for online personalisation. Studies have predicted double digit growth rates in the EU data market in terms of market value in the period up to 2020^{463} .

⁴⁶³ See for example the "European Data Market Monitoring Tool"²⁴³.

8.1.2. B) Consumers' awareness and perception of online personalised practices and problems experienced

Consumers' awareness of online personalised practices

The study shows that consumers' **self-reported awareness that online personalised pricing occurs is much lower than their awareness that online targeted advertising and personalised ranking of offers occurs**. Close to two thirds (67%) of EU28 respondents in the consumer survey indicated that they understood or had some understanding of online targeted advertising. For personalised ranking of offers the comparable figure was 62%, whereas for personalised pricing this was 44% only.

Consumers may have lower awareness of personalised pricing compared to personalised ranking of offers, because the latter may be a relatively more common practice, consistent with the findings of the mystery shopping exercise and literature review. Another explanation for the low awareness about personalised pricing might be that it is difficult for consumers to actually identify price discrimination when it occurs, as confirmed by the behavioural experiment⁴⁶⁴.

The findings from the behavioural experiment⁴⁶⁵ show that **self-declared awareness does not necessarily translate to an ability to correctly identify online personalisation.** In the behavioural experiment the proportion of respondents who correctly identified online targeted adverts, personalised ranking of offers, or personalised pricing was less than 50% for all practices. For example, less than 20% of participants in the behavioural experiment correctly identified price personalisation when they experienced prices which were lowered based on the participants' previous search history. Moreover, approximately only four in ten participants were able to correctly identify that an advertisement was present or correctly identified the product shown in targeted advertising.

The consumer survey and the behavioural experiment found that **potentially vulnerable consumers**, such as older people, those with low educational attainment, those having difficulty making ends meet, or those inexperienced with online shopping, have **lower overall awareness of personalisation**. For example, in the behavioural experiment, only 36% of those participants aged 65+ reported awareness of personalisation when asked if there were amongst those participants who had experienced personalisation in the experiment, compared to 49% of participants aged 16-34.

In the behavioural experiment participants tended to report greater awareness of personalised ranking of offers if they received more transparent

⁴⁶⁴ For example, less than 40% and less than 20% of participants in the behavioural experiment correctly identified price personalisation when they experienced prices which were either increased or lowered respectively, based on the participants' previous search history.

⁴⁶⁵ The behavioural experiment took place in exactly the same Member States that the Mystery Shopping did. It simulated an online search platform where participants were asked to purchase one of eight products listed there, based on information about their previous, similar searches/purchases. In the experiment, participants were randomly allocated to one of the following types of personalisation scenarios:

The 'baseline' or 'no personalisation' scenario, where the search results shown were presented randomly;

Personalised ranking of offers – where the ranking of offers shown were the ranking of offers.

Personalised ranking of offers – where the ranking of offers shown was tailored to participants based on their previous search history or browser;

Price discrimination – where participants were shown either higher, or lower, prices for the same product depending on their previous search history; and

Targeted advertising – where participants were shown a targeted advertisement, combined with either random sorting of search results, or results sorted based on their previous search history.

The behavioural experiment also tested the impact of treatments varying how transparently personalisation was communicated to participants.

Low transparency: where it was not made clear to the participant that results were personalised;

High transparency: where participants received salient communication that results were personalised to them: and

[•] High transparency + action: where participants received salient communication of personalisation, and it was easier for them to clear cookies and search again by a one click button.

communication explaining that results were somehow personalised to them based on their previous searches. The introduction of more transparency in communication by the online platform led to a statistically significant increase in the proportion of participants in the experiment *believing* – independent of whether this was true or not – that the products offered to them were ranked based on the previous search information shown to them.

Similarly, the proportion of participants in the experiment correctly identifying personalised ranking of offers when it occurred significantly increased as communication transparency about these practises increased. For example, among participants allocated to car rentals, on average 38% of the participants in the higher communication transparency treatments (where they were informed by the online platform about seeing results based on their previous searches/purchases) correctly reported that personalisation did occur, compared to 28% of participants who correctly reported that personalisation had occurred in the low communication transparency treatment (where no information was provided to the participant on the personalisation practice). However, there was very little difference in the proportion of respondents correctly answering whether they have experienced personalised pricing or targeted advertising, as transparency in the communication increased.

In the behavioural experiment, **potentially vulnerable** participants such as the economically inactive, those with difficulty making ends meet, and participants with low experience of online transactions **benefited most in terms of their awareness being raised due to more transparency in communication** by the online platform about the personalisation practices. For instance, 39% of economically inactive participants reported awareness of personalisation in the low communication transparency treatment when asked whether they were amongst the respondents who experienced personalisation. But this proportion increased to 46% in the higher communication transparency treatments. With older respondents (65+) this was even more profound: 28% in the low transparency treatment to 44% in the highest transparency treatment.

• Consumers' perception of online personalised practices

The study's results show that there is a substantial level of concern about online personalisation. Notably, for each of the three personalisation practices, less than 10% of survey respondents indicated that they did not have any concerns whatsoever.

- 1. A substantial proportion of consumers do not perceive any benefits of online personalisation: The share of respondents in the consumer survey who did not perceive any benefits ranged from 24% for targeted adverts, to 25% for personalised ranking of offers, and 32% for personalised pricing.
- 2. Across online personalisation practices, EU28 respondents in the consumer survey were most concerned about their personal data being used for other purposes or not knowing with whom this personal data is shared. For example, when asked about this in relation to *online targeted advertising*, around half (49%) of all survey respondents answered that they were concerned that their personal data could be used for other purposes and/or shared with others/3rd parties. This proportion was 46% in relation to personalised ranking of offers and 36% in personalised pricing respectively. Equally, concerns about users' data collected in order to make a profile out of them ranked particularly high (33% 46%). A substantial proportion of respondents (16%-25%, depending on the online personalisation practice) indicated as one of their three main concerns that they cannot refuse/ prevent online personalisation.
- 3. In the behavioural experiment, in line with the consumer survey, across all scenarios, the main reason for participants to have negative feelings about personalisation (indicated by approximately half of the respondents with negative feelings about personalisation) related to them feeling that their browsing data should be kept private, and that consumers do not like websites building profiles of their online behaviour and habits. There were also concerns about with whom

personal data could be shared, and that companies could use consumers' personal data for purposes other than the ones for which the data was gathered.

Nonetheless, the findings from the consumer survey, behavioural experiment and stakeholder survey suggest that a (relative) majority of consumers see both benefits and disadvantages of online personalisation. This applies in particular to online targeted advertising and personalised ranking of offers; opinions about personalised pricing tilted more to the negative. Approximately half of respondents in the consumer survey reported that they see both disadvantages and advantages for either targeted adverts or personalised ranking of offers, whereas this was the case with only 1 in 3 respondents for personalised pricing.

Participants in the behavioural experiment tended to agree more with positive statements about online personalisation compared to negative statements; this was driven mostly by the fact that they believed personalisation reduced their search time or because of being offered relevant products. In line with these findings, the results from the stakeholder survey point to a moderate level of consumer concerns about online personalisation. The combined results for the data protection authorities (DPAs) and consumer protection authorities (CPAs) stakeholder surveys showed that most stakeholders believe that consumers are either "somewhat concerned" (7 out of 19) or "little concerned" (6 out 19).

The consumer survey and behavioural experiment showed that **consumers consider the main benefit of online personalised ranking of offers and targeted adverts to be that they allow sellers to offer relevant and targeted products**. When asked about the benefits of *online targeted adverts* and *personalised ranking of offers*, across the EU28, respectively 42% and 34% of all respondents in the consumer survey reported as the main benefits of these personalisation practices that they allow them to see the products that they might be interested in.

- For targeted advertising, reducing the number of irrelevant ads seen was reported by 23% of EU28 respondents as the second main benefit, whereas for personalised ranking of offers 23% of EU28 respondents reported that this practice saves them time when searching online.
- When it comes to personalised pricing, the most important perceived benefits reported were that it allows online firms to offer reductions/promotions (22%) and that consumers can get the best available price for products (21%).
- For those participants in the behavioural experiment who reported that they realised during the experiment that there was personalisation, the statements with the highest agreement were "I found it useful to the overall purchase process" and "I liked it as my needs were catered for", with scores of approximately 3.4 (in a scale from 1 to 5). These scores were significantly higher than for the statements "I found it intrusive" and "I was upset" (2.6 and 2.3 respectively, in a scale from 1 to 5).
- The finding that online personalisation is not rejected a priori by consumers can also be deduced from the purchasing behaviour observed in the experiment. Participants in the experiment who believed that they had experienced personalisation were not significantly less likely to purchase a product, compared to those who did not believe, or did not know whether, personalisation had occurred. On average, 73% of respondents chose to purchase a product, whereas 27% chose to end the behavioural task without making a purchase. In addition, there was usually no significant difference in the probability of purchasing products (or which products they purchased) depending on the level of transparency in the communication on behalf of the online platform.

Nonetheless, in three particular scenarios of the behavioural experiment when personalisation was not communicated transparently, personalisation had an

impact on the probability that a personalised product⁴⁶⁶ **was selected by participants**. More specifically, in targeted advertising combined with personalised ranking of offers, 62% of participants chose to purchase a personalised product compared to only 50% in the no personalisation baseline scenario. In the price discrimination scenario where participants were shown lower prices, 66% of them chose to purchase a personalised product. In contrast, in the price discrimination scenario where participants where shown higher prices, only 37% of participants (as opposed to 50% in the no personalisation baseline scenario) purchased a personalised product. This was the case in the low transparency treatment only, where there was no salient communication that personalisation was taking place.

In general, when behavioural experiment participants purchased a product, the most frequently indicated reasons were because they thought that the price was fair, it matched their criteria or they liked the look/features of the good/service. There was also no statistically significant difference in the proportion of participants purchasing products between potentially vulnerable participants and others, with one exception. Participants who were relatively inexperienced with online transactions were significantly less likely to purchase products than others (on average 60% of this group purchased a product, across all treatments, while the average probability of purchase was 73%). In addition, the proportion of inexperienced participants purchasing products increased significantly as transparency of communication about personalisation increased.

How could consumers' concerns about online personalisation be mitigated? The research findings indicate that **consumers would be more positive about online personalisation if they received more information about these practices when they occur, and if they had more control of their online personal data.** About six in ten (62%) respondents in the consumer survey said that they would be more positive about online personalised practices if there would be an easy option to refuse/prevent these personalisation practices. Slightly more than half (52%-55%) of respondents said that they would be more positive if:

- 1. it was explained what personal data was collected about them;
- 2. they could see/change their personal data used for such practices;
- 3. it was explained for what purpose their personal data is collected; and
- 4. it was explained which 3rd parties access their personal data.

Slightly fewer (47%) respondents said that they would be more positive if they were informed when targeted adverts or personalised pricing/offers are shown to them and if they were informed why an advert or a search result/price was shown to them.

• Consumers' bad experiences with online personalised practices

The proportion of EU28 respondents in the consumer survey who reported to have had actual (a) bad experience(s) with the applicable personalised practices was quite substantial.

• Of all respondents, 18% reported bad experiences with online targeted adverts, 14% for online personalised ranking of offers, and less so (12%) for online personalised pricing. For respondents who indicated to understand these practices these figures were notably higher: for this group, 21% reported to have had a bad experience with targeted adverts, 18% reported to have had a bad experience with personalised ranking of offers, and 20% reported to have had a bad experience with personalised pricing. Hence, there appears to be a relation between awareness and the number of bad experiences reported. It should be kept in mind, however, that respondents who claim to be aware about personalisation practices do not

⁴⁶⁶ Personalised products were targeted to respondents based on their previous online behaviour and placed prominently in positions 1-3 of all ranked products.

necessarily correctly identify these practises, as shown in the behavioural experiment (see above).

- Among the quarter (25%) of those survey respondents who reported bad experiences, the most frequently reported bad experience was having been offered a product they were not or no longer interested in (50% of respondents with bad experiences reported this). Roughly a quarter (27%) of respondents with a bad experience with online personalisation reported that they ended up paying more for something they bought, whereas slightly less than a quarter (24%) mentioned that they were shown inappropriate adverts.
- When asked if they complained about their bad experiences, almost three quarters (73%) of respondents in the consumer survey said they did not do so. If complaining about bad experiences with online personalisation, respondents most frequently addressed the website involved or a national consumer organisation (10% and 6%, respectively, of all respondents with bad experiences indicated they did so). The stakeholder survey confirmed that most consumers do not complain about their bad experiences with online personalised practices⁴⁶⁷.

8.1.3. C) Assessment of whether businesses are transparent about online personalisation and comply with the existing regulatory framework

The consumer survey and mystery shopping exercise point to a lack of transparency about online personalisation by online business operators. For example, in total, 11 out of 17 (65%) data protection and consumer protection authority respondents noted that usually business operators are not informing consumers in a transparent manner about the collection and processing of their personal data. In addition, most DPA stakeholders reported cases where online firms failed to provide adequate information to consumers (e.g. incomplete or misleading information clauses) and failed to obtain an informed consent from consumers in relation to data processing. These findings were confirmed by the mystery shopping exercise:

- 1. Shoppers could not find any information about why they were shown targeted adverts during almost two thirds (65%) of the website visits during which they believed to have observed targeted adverts.
- 2. In only less than one in ten (9%) of the website visits for which targeted adverts were reported, shoppers were able to find information near the advert explicitly stating that it was personalised.

It should be emphasised that the study's findings cannot provide conclusive evidence on the actual level of compliance by online business operators. Depending on the country, DPAs are not necessarily the competent authorities to enforce Article 5(3) of the ePrivacy Directive⁴⁶⁸ and may hence not be able to provide accurate information on online firms' compliance with the EU data protection framework. Moreover, mystery shoppers may have missed more subtle information about why they were shown personalised results.

Overall, the stakeholder consultation showed that the vast majority of DPA respondents have rarely or never received complaints from citizens about personalised pricing/offers (10 out of 12). It should also be noted that most consulted CPA stakeholders indicated to only rarely have received complaints from consumers about online business operators' possible non-compliance with consumer law and the EU regulatory framework. On the occasions that they do, these relate mostly to complaints about consumers' personal data

⁴⁶⁸ The EU legal framework requires the user's consent before information can be stored or accessed on the user's device.

⁴⁶⁷ Most DPA and CPA stakeholders indicated that they rarely or never receive complaints from consumers about online personalised pricing/offers practices. It should be noted, however, that that DPAs are not necessarily the competent authorities to enforce Directive 2002/58/EC, which might explain the low number of consumer complaints about online personalisation they receive. See also below.

being used for other purposes. Nonetheless, the fact that they don't complain about them does not necessarily mean that they don't experience such practices, as shown in the consumer survey. Also, one needs to take into consideration the rather low awareness rate about the nature of personalised practices, especially personalised pricing. On the other hand, in the business operators' survey, most (7 out of 10) respondents from online firms claimed to be either "almost ready" or "in the process of implementing" the appropriate measures to ensure full compliance with the General Data Protection Regulation (GDPR) ⁴⁶⁹

However, even if online business operators would comply, the question remains what this would mean in practice for consumers. E-commerce firms and national experts in the stakeholder survey noted that although consumers are usually informed about personalisation and data collection via privacy statements, these statements are rarely read due to their length and the potentially complex language used. Similarly, it was noted by the stakeholders that consumers seldom take advantage of options to access, approve, edit or request the deletion of collected personal data, because doing so is not necessarily straightforward. In this respect, it should be mentioned that in the consumer survey:

- 1. Only four in ten (41% of) respondents indicated that, in their experience, all or most websites offer the possibility to refuse cookies.
- 2. Roughly a third (35%) respondents, on the other hand, reported that in their experience just some or only a few websites allow to refuse cookies.

Likewise, in the mystery shopping, in less than a quarter (22%) of the mystery shopping visits it was possible to refuse cookies, as reported by the shoppers.

8.1.4. D) Economic effects of online personalisation on consumers and sellers

There is no doubt that the collection of personal data and the profiling of consumers is enabled by the amount of data generated by multiple devices and the advances in tracking technologies and data analytics. This offers online sellers the possibility to offer consumers tailored (personalised) products and services and to be in a position to determine with greater accuracy the prices that consumers are prepared to pay according to their characteristics (e.g. affluent versus non-affluent shoppers) so as to better optimize their own revenues.

In this context, the behavioural experiment found that⁴⁷⁰ when communication about personalisation was less transparent, participants were significantly more likely to purchase the personalised products (compared to a baseline case of no personalisation) when they faced substantial personalisation, such as e.g. targeted advertising combined with personalised ranking of search results. This aligns with existing evidence showing that online personalisation can 'work' from the perspective of the seller. For example, existing evidence⁴⁷¹ suggests that behaviourally targeted advertising increases by more than fivefold the percentage of website visitors who complete a transaction: 3.8% compared to an average of 0.7% for un-targeted advertising. Therefore, the benefits on the use of personalisation are obvious for online firms. But to what extent does online personalisation bring benefits to the consumer and lead to higher consumer surplus?

The existing literature suggests that online personalisation in theory can benefit consumers if it matches them to products that best suit their needs, lowers prices and reduces their search costs. However, personalisation can negatively affect consumers if it is used to steer them towards the most expensive products that they are willing to pay for. In turn, personalisation may benefit consumers who actively shop around and are tech-savvy. This

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⁴⁶⁹ Available at http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R0679&from=EN

⁴⁷⁰ Although there was usually no significant difference in the probability of purchasing products overall, irrespective of the level of transparency in the communication of personalization on behalf of the online platform.

⁴⁷¹ IHM Markit, 2017.

is because, by comparing products between different online sellers, they are more likely to have a better knowledge of the online market and are therefore more likely to detect unfavourable personalisation or benefit from favourable personalisation when it occurs. However, personalisation, can harm consumers who are not able or willing to search due to for example time constraints, or those who have a high willingness-to-pay.

Market features may also play a role in the impact of personalisation on the allocation of welfare between sellers and consumers. For example, in markets with intense competition personalisation can benefit consumers since sellers can compete amongst each other to adapt their prices and win consumers with a lower willingness to pay. However, in markets with weaker competition online personalisation can help sellers to extract more surplus from online transactions, which can be detrimental to consumers. Engaged consumers can also exert pressure on sellers and retain consumer surplus. Existing research shows that when consumers are aware of online personalisation and feel that it is unfair, they can be turned away from those online sellers who engage in these practices. However, in reality the evidence of the behavioural experiment shows that consumers have a relatively low ability to identify online personalisation. In addition, the argument assumes that consumers take action to protect their data, which may not be the case in reality, as suggested by the consumer and stakeholder surveys.

In addition to impacts on welfare allocation for online transactions, online personalisation may have wider long-term impacts. For example, price discrimination practices, by allowing firms to seize a greater share of surplus from transactions, can in theory lead to more investment in innovation. On the other hand, online personalisation can limit the range of products available to consumers, hence raising barriers to competition and innovation. For example, targeted advertising to consumers based on their past purchasing behaviour (after the consumer has already purchased a similar product) or preferences could lead to conservatism in consumers' buying behaviour, preventing sales in other market sectors. Personalisation can effectively reduce consumer choice as a driver of competition, by directing consumers to options suggested by algorithms using consumers' previous buying/browsing data.

8.2. Policy approaches

The suggested policy approaches presented below should be seen in the light of the upcoming General Data Protection Regulation (GDPR) and the reform of the ePrivacy Directive⁴⁷². Since the GDPR strengthens the EU personal data protection framework and enforces the transparency and consent requirements for organisations processing personal data towards data subjects, it is advisable to first assess its impact on businesses and personalisation practices as it comes into effect on the 25 May 2018. In addition, the new ePrivacy Directive (under revision at the time this study was conducted) will maintain the consent requirements in relation to storing/accessing information on users' devices, unless one of the exceptions applies.

Based on the study findings, the following policy approaches could be considered:

1. The study suggests that the distinction between non-personal and personal data has become less clear, notably because online firms can collect data in a number of ways, and data that is not categorised as 'personal' can still be used to identify individual consumers. As the GDPR is based on the distinction between personal and non-personal data, the blurring of personal and non-personal data could impact enforcement of the GDPR. Hence this aspect could be further explored in the accompanying guidance and implementation measures for the GDPR.

European Parliament Research Service (EPRS) 2017, Review of the ePrivacy Directive, Briefing. Available at: http://www.europarl.europa.eu/thinktank/en/document.html?reference=EPRS_BRI(2017)587347

- 2. The GDPR specifies the type of language that would ensure the provision of transparent information. Nevertheless, the latest research⁴⁷³ suggests that privacy notices are not sufficient and that "privacy nudges"⁴⁷⁴ have the potential to better help users overcome behavioural biases that may impact their privacy and security related decisions. Therefore, best practices could be established for the design and use of privacy nudges related to personalisation practices.
- 3. A guidance providing clarifications specific to personalisation practices and the extent to which they fall within Art 22 of the GDPR on automated decision-making could be developed, building on the guidelines in Article 29 Data Protection Working Party on automated decision-making and profiling.

Enforcement by authorities

The study showed that competent authorities do not undertake enforcement actions in relation to personalisation practices due to the low number of complaints received from consumers. The following enforcement actions could be foreseen to monitor the development of personalisation practices in online markets:

- 4. Competent authorities such as DPAs and CPAs could take initiatives at Member State and EU level to increase cooperation and exchange of information in order to monitor personalisation practices occurring in the e-commerce environment and enforce compliance with relevant legislation.
- 5. Actions to enforce the GDPR rules and ePrivacy Directive with respect to privacy notices and the obligations of online traders and platforms to transparently inform consumers about the use of personalisation practices.
- 6. Actions to enforce the relevant consumer protection legislation in relation to unfair commercial practices and privacy notices (for example misleading omissions).

Self-regulatory actions

Reinforcing trust in, and transparency of, personalisation practices is essential to allow consumers to benefit from online personalisation. The findings from the study show that online personalisation can potentially be economically beneficial for both consumers and businesses. However, this requires consumers to trust online firms. Consumers' major concerns about online personalisation related to fears about data being used to build an online profile or being used for unauthorised purposes, as shown by the consumer survey and behavioural experiment.

The e-commerce industry could self-regulate on a voluntary basis in order to build and maintain consumer trust in the online market and complement existing legislation with additional standards.

7. This rapidly developing industry could agree to develop EU-wide standards and best practices on using personalisation practices in compliance with the EU data protection, privacy and consumer protection legal framework. Such actions could be streamlined through high-level European e-commerce organisations and associations that consist of different online traders and platforms such as Ecommerce Europe, the Interactive Advertising Bureau (IAB), the European

⁴⁷⁴ A "nudge" refers to choice architecture that "...alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives". Putting fruit at eye level would qualify as a nudge, whilst banning fruit does not. See Thaler, R. H. and Sunstein, C. R., 'Nudge: Improving Decisions about Health, Wealth, and Happiness', Yale University Press (2008).

⁴⁷³ See for example Shara Monteleone et al., 'Nudges to privacy behaviour: Exploring an alternative approach to Privacy Notices', Joint Research Centre, European Commission (2015). Available here: http://publications.jrc.ec.europa.eu/repository/bitstream/JRC96695/jrc96695.pdf

Advertising Standards Alliance (EASA), the European eCommerce and Omni-Channel Trade Association (EMOTA).

Increasing awareness among consumers

The results from the consumer survey and the behavioural experiments show that consumers' awareness of personalisation practices is low and that consumers experience difficulties identifying personalised offers/prices and targeted advertising. The behavioural experiment additionally showed that personalisation had an impact on the probability that a personalised product was selected by participants. The impact of personalisation on consumer's behaviour points to the potential relevance of increasing awareness. Even though the stakeholder consultation demonstrated that awareness-raising campaigns have already been launched on the topic in some countries, these developments are only recent. Moreover, consumers seem to have limited knowledge of the tools available to them to prevent more sophisticated tracking technologies online.

- 8. National governments, in cooperation with other competent authorities or stakeholders (i.e. CPAs, DPAs), could initiate information campaigns educating consumers on how to use basic and more sophisticated tools and instruments to detect and prevent online tracking.
- 9. Consumer associations/organisations could also be supported in conducting awareness-raising campaigns about personalisation practices and the available anti-tracking tools for consumers.

Policy approaches for further research

The study shows that advances in algorithmic pricing, profiling and "Big Data" will almost certainly further increase the prevalence and impact of online personalisation practices. However, the knowledge of the impact of these practices on consumer behaviour and consumer protection is limited for the moment. Therefore, further research could help to gain better understanding of the topic by examining the following key areas:

- 10. Research and development of specific tools with the objective to enable competent authorities to detect online personalisation practices more easily. Consumers could potentially also use these tools to detect and limit profiling (see for example existing tools such as "\$heriff", described in this study). According to the consumer survey, consumers value options that offer them the possibility to obtain more information about the use of their personal data for personalisation. However, these tools should be user-friendly; the evidence from, among others, the consumer survey in this study shows that if this is not the case, consumers will not use them.
- 11. Research aimed at detecting practices where online traders exploit the parameters of personalisation algorithms to influence consumers' purchasing decisions. The goal of such research would be to identify possible consumer impacts from algorithms codes exploiting behavioural biases to influence consumers' behaviour and preferences.
- 12. Research into smart disclosure methods and privacy nudges in order to improve consumers' awareness of personalisation practices.
- 13. Further legal assessment of the compliance of online tracking technologies used for personalisation practices with the relevant data protection and e-privacy legislation, including any potential gap identification in the current regulatory framework.
- 14. Further legal assessment of the transparency of personalisation practices with respect to the applicable data protection and consumer protection legal framework.

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15. Research focused on the impact of personalised pricing/offers on competition and the ability of consumers to make informed choices online. Further research also on aspects impacting consumers' welfare, namely on the quantitative impact of online personalisation on consumers' search costs and quality of product matches.

