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Economics of Privacy:

Users' Attitudes and Economic Impact of Information Privacy Protection

a dissertation submitted to the doctoral school of economics and management in partial fulfillment of the requirements for the Doctoral degree (Ph.D.) in Economics and Management

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Acknowledgements

"Life begins at the end of your comfort zone",

- Neale Donald Walsch

I have always wanted to become a designer. God knows how I ended up at the faculty of economics instead. Honestly, I was not particularly excited about that... until I went to the University of Trento under the Erasmus Mundus exchange program, where I discovered (and immediately fell in love with) a very special branch of this science. I'm very grateful to prof. Luigi Mittone for introducing me to the world of behavioral and experimental economics, for encouraging me to apply for a doctoral program in this field that eventually became my life, and for supporting me along the way.

The first year of doctoral program was just a hell: sleepless nights, tons of new reading material, weekly assignments of advanced level of complexity, sore muscles and itchy eyes after a whole day in front of a computer. Who knows whether I could make it through without a kind support of my dear classmates and colleagues. Together preparing for the exams and solving the most difficult exercises we managed to survive the first year. Special thanks to my friend and experienced researcher, Marco Ajelli, who could spend the whole day working through the thick textbook of statistics with me and patiently explaining the unclear concepts, or helping to write a code for computer simulations for a course project.

A third of the first summer vacation I spent at the summer research camp. In contrast to the majority of summer schools, which usually happen somewhere on a beautiful Greek island or at least close to the public beach of Barcelona and last about a week, the IMPRS summer school in Uncertainty and Decision-Making takes place in a small German city called Jena and lasts for a month. It was a taught, intense, and, ultimately, extremely valuable experience. I acquired many new skills and was lucky to meet Alexia Gaudeul, who became my informal research mentor and co-author of the first scientific paper. I am very grateful to her for close attention to my work, patient guiding of my first steps in the academic career, and a substantial selfless contribution in upbringing me as a researcher.

The second year of doctoral program threw us into the sea of nearly independent research. Suddenly we moved from the joint lectures and group assignments to our small offices and started to work independently, each focused on her own project. I was lucky to get a desk in the Cognitive and Experimental Economics Lab (CEEL) in a cozy attic with a beautiful wooden ceiling and a small window looking at the top of Monte Bondone. Although the diverging research interests and chronic lack of time inevitably reduced our social interaction with classmates, at the same time it tied us tightly with an officemate (and subsequently a dear friend). Thank you, Nives Della Valle, for our five o'clock teas and stretching sessions, for watering my plants, and personal support. Whatever road you choose, I wish you success, satisfaction, and peace of mind.

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That being said, I was enjoying what I was doing so far, but till a while ago I was not sure whether I was doing the right thing, whether I should stay in academia or search for a job in the industry, dedicate the whole life to research or switch to a completely different field and start everything from scratch. Now, by the end of the PhD program, I feel more comfortable and convinced that

what I am doing is positively contributing to my own future and hopefully to the future of the society. I wanted to design – I do design, of the experiments and research studies for now. I'm adding on the User Experience and Interface Design knowledge and skills. I'm discovering the forms of design that I was not even aware before. I realize that both fields, Design and Social Sciences, have a lot in common and share the similar methodology, and that all the time I was confused about diverging away from my dream, I was actually enriching my background and knowledge base. Hence, when I will eventually arrive to the field of design full scale, it would be a lot different and qualitatively better high-grade research-based design approach.

Although the PhD thesis project is a tough three-year long thorough work on a very narrow research topic, full of obstacles, required huge commitment, self-discipline, effort, and perseverance, once it is completed, a number of possibilities, opportunities, and doors, which would be otherwise inaccessible, are opening in front of you. The journey continues. I do not need to start all over again, I can choose your way more freely and make any desired transition smoothly to continue self-development in multiple directions, always keeping in mind my dream and pursuing the main goal. I can go ahead expanding the horizon. I hope to be strong enough to push the boundaries even further and always continue growing, learning something new, and conquer new heights.

Abstract

This doctoral thesis consists of three essays within the field of economics of information privacy examined through the lens of behavioral and experimental economics.

Rapid development and expansion of Internet, mobile and network technologies in the last decades has provided multitudinous opportunities and benefits to both business and society proposing the customized services and personalized offers at a relatively low price and high speed. However, such innovations and progress have also created complex and hazardous issues. One of the main problems is related to the management of extensive flows of information, containing terabytes of personal data. Collection, storage, analysis, and sharing of this information imply risks and trigger users' concerns that range from nearly harmless to significantly pernicious, including tracking of online behavior and location, intrusive or unsolicited marketing, price discrimination, surveillance, hacking attacks, fraud, and identity theft. Some users ignore these issues or at least do not take an action to protect their online privacy. Others try to limit their activity in Internet, which in turn may inhibit the online shopping acceptance. Yet another group of users gathers personal information protection, for example, by deploying the privacy-enhancing technologies, *e.g.,* ad-blockers, e-mail encryption, *etc.* The ad-blockers sometimes reduce the revenue of online publishers, which provide the content to their users for free and do not receive the income from advertisers in case the user has blocked ads. The economics of privacy studies the trade-offs related to the positive and negative economic consequences of personal information use by data subjects and its protection by data holders and aims at balancing the interests of both parties optimizing the expected utilities of various stakeholders. As technology is penetrating every aspect of human life raising numerous privacy issues and affecting a large number of interested parties, including business, policy-makers, and legislative regulators, the outcome of this research is expected to have a great impact on individual economic markets, consumers, and society as a whole.

The first essay provides an extensive literature review and combines the theoretical and empirical evidence on the impact of advertising in both traditional and digital media in order to gain the insights about the effects of ad-blocking privacy-enhancing technologies on consumers' welfare. It first studies the views of the main schools of advertising, informative and persuasive. The informative school of advertising emphasizes the positive effects of advertising on sales,

competition, product quality, and consumers' utility and satisfaction by matching buyers to sellers, informing the potential customers about available goods and enhancing their informed purchasing decisions. In contrast, the advocates of persuasive school view advertising as a generator of irrational brand loyalty that distorts consumers' preferences, inflates product prices, and creates entry barriers. I pay special attention to the targeted advertising, which is typically assumed to have a positive impact on consumers' welfare if it does not cause the decrease of product quality and does not involve the extraction of consumers' surplus through the exploitation of reservation price for discriminating activities. Moreover, the utility of personalized advertising appears to be a function of its accuracy: the more relevant is a targeted offer, the more valuable it is for the customer. I then review the effects of online advertising on the main stakeholders and users and show that the low cost of online advertising leads to excessive advertising volumes causing information overload, psychological discomfort and reactance, privacy concerns, decreased exploration activities and opinion diversity, and market inefficiency. Finally, as ad-blocking technologies filter advertising content and limit advertising exposure, I analyze the consequences of ad-blocking deployment through the lens of the models on advertising restrictions. The control of advertising volume and its partial restriction would benefit both consumers and businesses more than a complete ban of advertising. For example, advertising exposure caps, which limit the number of times that the same ad is to be shown to a particular user, general reduction of the advertising slots, control of the advertising quality standards, and limitation of tracking would result in a better market equilibrium than can offer an arms race of ad-blockers and anti-ad-blockers. Finally, I review the solutions alternative to the blocking of advertising content, which include self-regulation, non-intrusive ads programs, paywall, intention economy approach that promotes business models, in which user initiates the trade and not the marketer, and active social movements aimed at increasing social awareness and consumer education.

The second essay describes a model of factors affecting Internet users' perceptions of websites' trustworthiness with respect to their privacy and the intentions to purchase from such websites. Using focus group method I calibrate a list of websites' attributes that represent those factors. Then I run an online survey with 117 adult participants to validate the research model. I find that privacy (including awareness, information collection and control practices), security, and reputation (including background and feedback) have strong effect on trust and willingness to buy, while website quality plays a marginal role. Although generally trustworthiness perceptions and purchase intentions are positively correlated, in some cases participants are likely to purchase from the websites that they have judged as untrustworthy. I discuss how behavioral biases and decision-making heuristics may explain this discrepancy between perceptions and behavioral intentions. Finally, I analyze and suggest what factors, particular websites' attributes, and individual characteristics have the strongest effect on hindering or advancing customers' trust and willingness to buy.

In the third essay I investigate the decision of experimental subjects to incur

the risk of revealing personal information to other participants. I do so by using a novel method to generate personal information that reliably induces privacy concerns in the laboratory. I show that individual decisions to incur privacy risk are correlated with decisions to incur monetary risk. I find that partially depriving subjects of control over the revelation of their personal information does not lead them to lose interest in protecting it. I also find that making subjects think of privacy decisions *after* financial decisions reduces their aversion to privacy risk. Finally, surveyed attitude to privacy and explicit willingness to pay or to accept payments for personal information correlate with willingness to incur privacy risk. Having shown that privacy loss can be assimilated to a monetary loss, I compare decisions to incur risk in privacy lotteries with risk attitude in monetary lotteries to derive estimates of the implicit monetary value of privacy. The average implicit monetary value of privacy is about equal to the average willingness to pay to protect private information, but the two measures do not correlate at the individual level. I conclude by underlining the need to know individual attitudes to risk to properly evaluate individual attitudes to privacy as such.

Keywords: information privacy, lab experiment, survey, online advertising, privacy-enhancing technologies, consumers' welfare, trust, purchase intentions, risk

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Chapter 1

The effects of advertising in traditional and digital media on consumers' welfare: Literature review

1.1 Introduction

In this chapter I will review the economic and marketing literature on advertising and apply it to the growing field of economics of privacy in order to analyze the effects of online advertising, and more specifically, of ad-blocking privacy-enhancing technologies, on consumers' welfare. In a broad sense, by ad blocking I mean filtering out advertising content on websites and in mobile applications. For the purpose of this literature review I will distinguish two large groups of advertising: online and offline. Offline advertising is usually delivered through traditional channels, such as print media, radio, and TV. Online (or web) advertising occurs in the Internet and is delivered to the consumers through digital channels, such as personal computer, tablet, or mobile phone. Interactive advertising, in particular, encourages active participation of a user in a marketing campaign. Although first interactive marketing campaigns appeared in the offline world as interactive billboards, storefront windows, kiosks, and vending machines, in the recent years the Internet took over the role of a main medium for interactive advertising by using social media channels and rich media ads, including pop-up and animated banner ads, videos, *etc.* In this chapter I will use terms online advertising, web advertising, and digital advertising interchangeably.

In the recent years online advertising has become a rapidly growing and important market for global economy. Internet advertising revenues in Europe has reached $41.1 billion in 2015 (Statista, 2015). In the end of 2015, U.S. online advertising revenue showed a 20% growth over the previous year and reached \$59.6 billion, accounting for about 29% of total worldwide advertising spending (Goodman, 2016). Mobile advertising manifested even more striking growth of 66% during the same period (IAB, 2016).

A large proportion of increased advertising revenue comes from the introduction and development of fine-grained user targeting based on the vast database of users' personal information and online activities, and from the more detailed analysis and reporting on advertising campaign performance. Empirical evidence that I will discuss in greater details in section 1.3 shows that targeting increases click-through and conversion rates (*e.g.*, Farahat and Bailey, 2012; Aziz and Telang, 2016). However, the extensive data collection and large volumes of customized and sophisticated ads raise concerns and nuisance among users. A number of surveys demonstrate that users generally are not supportive of targeting and not comfortable with behavioral advertising (*e.g.*, Turow et al., 2009; Morales, 2010; Eurobarometer, 2015). In response to invasive advertising strategies, some users adopt technological solutions that help to remove advertising content from the visited websites and protect users from tracking of their online behaviors.

Online advertising ecosystem continuously expands and claims to generate economic wealth in a form of both, advertising revenues and increased product and service sales, as well as to improve customer satisfaction through better buyer-seller matching. However, it remains to a large extent unclear how this wealth is distributed among advertising ecosystem stakeholders and how the technologies deployed for users' data mining, subsequent ad targeting, and advertising delivery affect consumers. Who appropriates the most of the generated wealth: advertisers through an upsurge in sales, ad-selling companies and publishers through increased revenues, or end users through augmented surplus? What are the negative effects of online advertising that are rarely spoken out in the industry reports? Does the value added by each element of this growing chain is proportional to the cost of the supplement? If not, may the rapid growth of digital advertising infrastructure turn into economic bubble? Is online advertising era as new as it is proclaimed to be or more than a century of marketing and economic research can help in predicting the trend of evolution and economic impact of digital advertising? Answers to these broad and sophisticated questions lie at the intersection of marketing, information systems, privacy, and economic fields.

In this chapter I focus on two main strands of literature: marketing literature on traditional advertising, and recent research on the digital economy, in order to address the following research question: what is the impact of ad-blocking privacy enhancing technologies on consumers' welfare? To gather the theories and findings that may be applied to the modern online advertising practices I first go to the roots of marketing research, analyzing the classic literature on advertising value and the economics of advertising. Then I describe the current situation in online advertising industry and the effects it has on the main players, including consumers, advertisers, publishers, and advertising companies. Additionally, I briefly review some advertising-related issues from psychological and legal perspective, including fiscal policy, limitation of the consumers' consideration set and exploration, cognitive and information overload, *etc.*

The chapter is organized as follows: section 1.2 introduces the most prominent schools of advertising and approaches of measuring the consumer surplus and welfare, provides an overview of theoretical predictions and empirical evidence about the effects of advertising and targeting in traditional media on consumers and net welfare, on product quality and consumer satisfaction, prices, competition, and market structure; section 1.3 analyzes state-of-the-art in online advertising industry, provides an overview of theoretical models and empirical evidence on the effects of advertising and behavioral targeting in digital media; section 1.4 summarizes the results of theoretical and empirical research on the effects of advertising restrictions, discusses how these results may help to predict the welfare implications of the modern privacy-enhancing technologies deployment, and suggests the alternative privacy-protecting solutions for regulating of the online advertising industry; and section 1.5 summarizes and discusses the results and concludes.

1.2 Advertising in traditional media

1.2.1 Views on advertising role

Over more than a hundred years of economic and marketing research on advertising, three views on the role of advertising have emerged: informative, persuasive, and complementary. It is believed that Marshall (1890, 1919) first distinguished between constructive role of advertising conveying information, and "socially wasteful" combative role of advertising redistributing customers from one company to others and creating artificial product differentiation. Started as a mere recognition of diversity of the functions that advertising performs, with time the difference in views led to completely separate schools of advertising, which based their models on distinct assumptions and therefore reached diverging conclusions. I start from the introduction of three main schools of advertising, and overview of their assumptions.

The main role of persuasive advertising is to influence the consumer choice in favor of the advertised brand and to create brand loyalty. The conceptual foundation of the persuasive view was first developed by Braithwaite (1928); Bain (1949); Packard (1957, 1960); Galbraith (1958, 1967); Comanor and Wilson (1967, 1974); Kotowitz and Mathewson (1979), and further advanced by Bloch and Manceau (1999); Tremblay and Martins-Filho (2001); Banerjee and Bandyopadhyay (2003); Chioveanu (2008); Baye and Morgan (2009), and others (for a more detailed review see Bagwell, 2007). Persuasive school advocates believe that advertising changes the utility function and tastes of buyers, distorts consumption quantities, increases market share of larger firms in expense of the smaller ones, augments concentration, leads to inelastic demand curve and higher prices, accompanied by decrease in quality and entry deterrence.

The main role of informative advertising, as suggested by its name, is to inform consumers about the product existence, characteristics, price, and where they can find and purchase it. The upraise of the adherents of the informative role of advertising dates back to the 1960-s, mostly among Chicago School economists, including Ozga (1960); Stigler (1961); Telser (1964); Nelson (1970, 1974); Verma (1980); Nichols (1985), *etc.* They believed that advertising affects the utility function only if contains valuable information for consumers, which removes the information asymmetry. However, while advertising (especially customized for consumers' preferences) may reduce consumers' search costs (Chellappa and Sin, 2005; Tam and Ho, 2006; Okazaki et al., 2009), some studies predict the equilibrium incline in favor of bigger firms (Bagwell, 2007), as such companies can afford a larger advertising volume.

Borden (1942b) warns that advertising "does not give consumers sufficient information to enable them to buy with full economic effectiveness" (p. 98). Nevertheless, he concludes that advertising, "though certainly not free from criticism, is an economic asset and not a liability" (p. 99). Kaldor (1950) suggests that subsidizing information delivery should benefit the society, as consumers tend to underestimate the value of knowledge when market information is not freely available. However, he criticizes the information provided in advertising to be often biased or deficient because it is "supplied by interested quarters", and, therefore, "impartial and unbiased information could only be provided if the writers of "advertisements" were financially independent of the products advertised" (p. 5). Based on the Kaldor's conclusion one may expect the contemporary phenomenon of user-generated content (*e.g.*, in a form of consumer reviews) to be a more socially desirable source of market information supply than professional advertising campaigns. However, the efficiency of such consumer feedback systems is limited by its ability to detect fraudulent reviews and prevent manipulation of the content. Regarding the economic effect on the market as a whole, informative view followers draw the pro-competitive effects of advertising, more elastic demand curve, decrease in price, and increase in product and service quality.

Interestingly, Nelson (1974) emphasizes that informative role of advertising is greater for search goods; while for experience goods it is largely mediated by increasing firm's reputability rather than through delivery of explicit information. In other words, information about search goods may help consumers to make a more informed (if not better) choice of a product, while the marginal value of supplied information about experience goods is limited because their characteristics, important for quality evaluation, are often not measurable or objective and can be assessed only after consumers' personal experience with the product. The producers and vendors of search goods can successfully use both informative and persuasive advertising. Once the customers have tried a certain experience or credence good, difference in the value of informative advertising for these types of products and search goods decreases, because experienced users now can derive the utility from the information about price, sales point location or discounts on the already familiar product. Therefore, search goods manufacturers benefit from employment of informative advertising more than manufacturers and sellers of experience and credence goods, which have to rely on rather persuasive advertising techniques to convince customers to try their products or services and then make a decision about repeated purchases.

The third, and most recent, complementary view on advertising, has not gained as much popularity as the two main approaches. According to complementary view, instead of merely influencing the utility, advertising enters the utility function directly, complementing the consumption (Fisher et al., 1979; Hochman et al., 1988; Wernerfelt, 1990; Becker and Murphy, 1993, *etc.*). This substantive value of advertising is usually associated with the notion of social prestige or image bundled with the purchased goods (Kaldor, 1950; Stigler, 1961; Pastine and Pastine, 2002; Clark and Horstmann, 2005; Chwe, 2013, *etc.*). In other words, when customer buys a product, she not only gets the physical object or service, but also appropriates the part of reputation associated with its brand constructed through the advertising messages. For example, brand advertising of Dior fashion house creates an image of their customers as wealthy upper middle class with refined taste and as experts of quality. People familiar with this brand (and not even necessarily possessing its products) are then likely to automatically judge the Dior bag's owner as wealthy person having good taste and appreciating high quality. Therefore, buying a genuine Dior bag, customer is paying not only for the materials and labor force used to produce this bag, but also for the social prestige that the use of a luxury product will transmit to others. This is true not only for the *haute couture* brands. The same logic can be applied to all different kinds of social images. For example, advertising makes it possible for general public to recognize the eco-friendly or health-aware social position signals of the owners of electric cars or people shopping in the grocery stores that sell only organic products. Complementary view assumes that such social recognition adds a direct value to the use of these cars and shopping in these stores.

My brief overview of the roles of advertising illustrates the insight that the impact of advertising is controversial because various schools derive distinct effects of advertising on price, market structure, competition, and utility function. As the goal of this study is focused on the analysis of advertising impact on consumers' welfare, I start the next section from the overview of models that attempt to measure consumer surplus, followed by the theoretical predictions about the impact of advertising on it according to various schools, and finally I investigate the empirical evidence of such effects.

1.2.2 Measurement of consumer surplus

In economic theory, social (or net) welfare is usually referred to as a sum of consumer surplus and business revenues. The compensating and equivalent variations based on the shift of the Hicksian compensated demand curve (Hicks, 1942) were adopted as traditional empirical measures of welfare change (see Slesnick (1998) for the review of alternative approaches). Compensating variation (CV) is the amount of money necessary to bring consumer back to the initial utility level after change in price or introduction of a new product or service. In other words, CV represents the dollar amount required to achieve the initial level of utility given the current prices, while equivalent variation (EV) is the amount required to preserve the initial prices to experience the current level of utility. These two measures were widely used for welfare analysis in traditional markets as well as for estimating welfare gain from IT investments (Bresnahan, 1986; Brynjolfsson, 1996), personal computer adoption (Rosston et al., 2011; Greenwood and Kopecky, 2013), proliferation of broadband (Greenstein and McDevitt, 2009; Nordhaus, 2015), increased product variety in the digital economy (Brynjolfsson et al., 2003), and specifically in e-commerce (Fan et al., 2015), *etc.*

Brynjolfsson (1996) reviews other three approaches to measuring consumers' surplus: the approach based on Marshallian demand curve, nonparametric approach, and the approach based on the theory of index numbers. They are less common because the approach based on Marshallian demand curve does not provide the exact welfare measure when the utility for consumers is kept constant and the price changes are relative; the nonparametric approach assumes income elasticity to be equal to one; and the approach based on the theory of index numbers makes assumptions about the form of the utility function rather than demand curve. Nevertheless, Brynjolfsson (1996) concludes that under accurate functional form assumptions and small income effects, various methods of consumers' surplus measurement result in similar estimates.

It may be possible that price variation for the products in organic and sponsored listings is low, while time spent on the searching of the products differ substantially between conditions with and without ads. On the one hand, online ads may distract users' attention and therefore increase the time she spends on searching for a product. On the other hand, ads may reduce searching costs by offering a shortcut to the customer, matching buyer to seller in a fast and efficient way, and reducing the time necessary to find an appropriate product. As the effect of advertising on product-searching time depends on a number of factors, *e.g.*, goal-oriented *versus* exploratory mode of the task (Shapiro et al., 1997; Danaher and Mullarkey, 2003), hedonic *versus* utilitarian goods, position in the purchasing funnel (Ghose and Todri, 2015; Hoban and Bucklin, 2015), I do not make any assumptions about sign of the difference, however, I consider time to be an important factor influencing the utility function.

A number of researchers suggested including time-related variables into the utility function for computing consumer surplus. For example, in attempt to measure the consumer surplus from Internet access, Goolsbee and Klenow (2006) criticize the standard approach of measuring consumer welfare in traditional markets for being inappropriate and, thus, welfare calculations being uncertain in application to the use of Internet. To account for the low (or equal to zero if monthly fee is fixed) marginal costs of Internet use and price variation that complicate the estimation of price elasticity from expenditures, authors introduce into expenditure function the value of time as a fraction spent in the Internet in relation to the wage. Alternative measure of elasticity is based on the opportunity cost of time (Hausman, 1981). Goolsbee and Klenow (2006) and Brynjolfsson and Oh (2012) deployed the time-use survey data for validation. The model of Goolsbee and Klenow (2006) was further developed by Hadhri et al. (2012), who allowed concavity of wage function and added non-income variables. The proposed models can be easily adopted for the context of online advertising. In the case of Goolsbee and Klenow (2006) model, for instance, instead of comparing the prices for Internet and composite goods, one should use the prices of products from organic and sponsored listings to compute the consumer surplus generated by the presence of ads (or by their absence due to the use of ad-blockers).

In the next section I review models and empirical evidence of advertising effect on consumer surplus first from a purely economic perspective. Then I discuss the extended models that include time costs and intangible components of consumer welfare, such as product quality, consumer quality perceptions, and satisfaction.

1.2.3 Effects of advertising

1.2.3.1 Effects of advertising on consumer and social welfare

According to Becker and Murphy (1993) consumer surplus generated by advertising is appropriated by the firms through increased direct sales. Even the early work of Braithwaite (1928) already views the manufacturing and selling costs as the "true cost of production", while advertising costs of creating reputation as a component that adds mostly "artificial value", substantially increases the final price, and makes demand curve less elastic. Therefore, a firm that uses advertising is more likely to be harmful for economic welfare than a monopoly that does not employ advertising. Consumers gain only in the case where introduction of advertising costs is accompanied by the reduction of production costs and, therefore, of final price, which according to the author is, however, unlikely to happen. Borden (1942a) in his extensive study of various commodities provides the evidence of the opposite: in many cases increased advertising costs are offset by lower production costs. Nevertheless, he acknowledges that the generalization of such conclusion is limited because sometimes the price for consumers increases due to advertising.

Although Braithwaite (1928) does not deny the potential "educative" and complementary effects of advertising, she argues that the vast majority of ads appeals to emotions rather than reasoning and that advantages related to the created firms' reputation do not countervail the detrimental effect on consumer surplus. The normative theory of persuasive ads predicts a growth of social welfare only if the monopolist decreases price and advertising volume (Dixit and Norman, 1978). His model is based on the assumption of positive relationships between advertising intensity, price, and sales. However, this assumption has spurious empirical support.

The complementary view advocate Kaldor (1950) argues that consumers buy not just a product, "but a miscellaneous collection of services as well, such as the assurance of quality as afforded by the reputation of the particular manufacturer" (p. 22-23). Because advertising value is directly included in the utility function, image-creating effect contributes to the consumer surplus gain (Fisher et al., 1979). However, the value added not always recoups the incremental cost and the ultimate impact on social welfare cannot be decided upon the economic theory alone:

> "If advertising is to be justified it must be by reference to its indirect consequences rather than to its direct benefits; it must be justified by demonstrating that improvements in productive and distributive efficiency resulting from advertising more than offset both the direct cost of advertising and the balance of further social losses caused by distortion of demand, *etc.*" (Kaldor, 1950, p. 7)

Similarly, Nichols (1985) states that the necessary condition for positive consumer benefit is the excess of "prestige productivity" over the price increase.

Butters (1977) shows that business and social benefits are not dependent on prices of products and ads under the assumption of identical consumer unit demand and informative advertising. This conclusion is derived from the fact that firms either appropriate consumer surplus but may not attract rival's customers when send a high-priced ad, or does not appropriate consumer surplus, but may steal customers from the rival firm when send an ad at a lower price. Extension of the model in Stegeman (1991) assumes heterogeneous consumer preferences and concludes that regardless of the ad price, increase in advertising level augments welfare.

Stahl (1994) finds negative relationship between advertising cost and consumer surplus and positive impact of convexity of advertising expenditures on consumer and social welfare, but not on producer surplus. Kaldor (1950) however supposes that the expansion of demand due to unequal intensity of advertising among rival firms should not significantly influence the consumer and total welfare.

Thus, as we can see, the conclusion about the effect of advertising on consumers' welfare largely depends on the assumptions about the role of advertising, ads' and products' prices, elasticity of consumers' demand function, *etc.* Moreover, the shift in demand curve may be caused by various factors, for example, due to stockpiling, change in the level of consumption, prices, savings, *etc.* Therefore, welfare outcome is influenced not only by the demand change itself but also by the factors that induce this shift. I further provide an overview of empirical evidence on the impact of such factors.

Expansion of demand due to price change Empirical analysis of the cross-sectional data on dog food and aluminum foil sales in Kanetkar et al. (1992) shows that advertising increases price elasticity and decreases prices. Sheng (2004) observed the general opposite effect in the Canadian accommodation market. However, he concludes that welfare implications depend on various factors, such as type of advertising (price *versus* non-price), revenue, and marginal costs. Namely, in line with Kaul and Wittink (1995), he found that price advertising increases price sensitivity and decreases prices.

Expansion of demand at the cost of savings Kaldor (1950) agrees that shift of the demand curve is possible due to increase in the general propensity to consume or use of intended savings. The reduction in savings is expected to be higher for the middle and upper class because saving rates of the lower class are inelastic. However, he claims "impossible to test this hypothesis statistically" and to measure the exact economic effect (p. 9).

Expansion of demand due to switching, redistribution, and other sales promotion effects Marketing literature provides an extensive research and empirical evidence of the effects of sales promotion. The most prominent effects of sales promotion are stockpiling, reduction of non-promotional retail sales and demand for competing brands, increased consumption, cross-category, brand and store substitution (Kumar and Leone, 1988; Walters, 1991; Bucklin and Lattin, 1992; Bell et al., 2002). Because advertising is one of the most popular approaches to the sales promotion, it carries out all of the above-mentioned effects. We will discuss them now in detail.

Due to stockpiling, retailers shift a part of inventory costs to consumers (Blattberg and Neslin, 1989). The evidence of stockpiling effect was found in a number of studies (see Shoemaker, 1979; Gupta, 1988; Blattberg and Neslin, 1989; Jain and Vilcassim, 1991; Bucklin and Gupta, 1992; Chintagunta, 1993; Neslin et al., 1995; Bucklin et al., 1998; Mela et al., 1998; Van Heerde et al., 2000; Macé and Neslin, 2004). Borden (1942a) argues that advertising does not directly shift the demand curve but rather "speed up the expansion of demand that naturally would have come without advertising, or check or retard an adverse trend" (p. 433-434). Indeed, without increase in consumption, stockpiling may be associated with either purchase acceleration, by moving earlier in time the purchasing event that would have been occurred anyway (Doyle and Saunders, 1985; Krishna, 1992), or purchase deceleration, because of consumers postponing the purchase due to expectations of promotion (Krishna, 1994; Gönül and Srinivasan, 1996; Mela et al., 1998). Both of these effects result in subsequent dip in sales. In contrast, the absence of the post-promotion sales decline may be related to the increased consumption, repeat purchases effect, and consumer inventory insensitivity (Neslin and Stone, 1996).

Increase in consumption is described through the three interrelated mechanisms: a larger number of purchasing occasions, fewer cases of stock out, and higher consumption rates. Early models assume constant usage rate. However, a flexible usage rate behaviorally is more reasonable (*e.g.*, Ailawadi and Neslin (1998) propose spline and continuous nonlinear functions[1]). Other potential reasons of the growth in consumption rates are related to a higher inventory capacity, and as consequence, to a higher flexibility of consumption at desired level (Assunção and Meyer, 1993) and higher awareness of the product within the household (Wansink and Deshpandé, 1994). The relation between inventory levels and consumption rates can be also explained by the "scarcity theory": people tend to value the smaller quantities more than bigger ones, and therefore,

[1]See also Bell et al. (1999); Silva-Risso et al. (1999).

to slow down the consumption with respect to desired level (Wansink, 1996). Finally, advertising attempts to encourage consumers to use products more often or at larger amount (*e.g.*, by suggesting to take two chewing gums at a time instead of one, and after every meal rather than once a day) also contributes to the growth of consumption rates.

Cross-category effects of promotion appear in a form of 1) complementarity, *e.g.*, buying a non-promotional tomato sauce together with promotional spaghetti pasta, and 2) substitution, *e.g.*, buying promotional spaghetti pasta instead of non-promotional elbow macaroni (Manchanda et al., 1999; Mulhern and Leone, 1991; Walters, 1991). Walters and MacKenzie (1988) showed that trade-off between the two effects results in the in-store fall of non-promotional sales.

The redistributive effects of advertising were acknowledged already in Marshall (1890, 1919). Kumar and Leone (1988) attribute store substitution to the cross-shopping ("cherry-picking"), especially for frequently purchased and high-priced products and to the store's offers of a particular promotional blend of products rather than featuring one single product. Their analysis of the store-level scanner data shows that price promotion leads to the most extensive brand substitution within a given store. However, they found the empirical evidence of store substitution only on a weekly level and for the stores within a relatively close geographic proximity.

The promotion effects described for traditional marketing channels directly apply to the era of online advertising, further expanding the horizon of effectiveness they may achieve. Shift to electronic trade and cloud storage has decreased the inventory and transaction costs and lead to an increase of consumption and stockpiling. Home libraries and multimedia collections are not limited by the size of a bookshelf anymore – electronic memory and cloud computing together with portable devices, such as smartphones, music players with Internet connection, electronic books, and tablets, made it possible to access vast amount of information at any time and from any place. Shopping has never been that easy. Amazon's "1-Click" buying technique that stores users' payment details for future purchases allows customers to buy online with only one click (Hartman et al., 1999). Amazon's Prime account offers free delivery, Netflix's subscription provides virtually unlimited access to its movie and TV shows library, further facilitating online shopping and decreasing transaction costs due to scaling up effects. Internet makes the advertising communication more prompt and fine-grained to the consumers' preferences. Information about promotions, newsletters, and stock availability is now more frequent and well-timed than before. Finally, sophisticated recommendation algorithms, accessibility of comparison shopping, and online product reviews facilitate cross-category, store- and brand-switching. On the other hand, a requirement to create an account on almost every website, smart design of platforms' architecture, and lock-in business models ensure customers' loyalty.

Existing models of welfare analysis often overlook or underestimate the above-mentioned effects of the marketing activities on the distribution of surplus. While companies are focused on calculation of the return on investment and on assessment of advertising campaign effectiveness, privacy advocates often disregard businesses' economic incentives in desire to protect consumers' benefits. Despite widely discussed intangible "harmful" effects of annoying and obtrusive advertising on consumers, the impact of advertising on their welfare lacks scrupulous research. This section highlighted that certain promotional activities result in mere reallocation of resources among business players (limited by consumers' budget constrains) without change in the net welfare (*e.g.*, due to store- and brand-switching, purchase acceleration and deceleration). Some other marketing activities lead to a real structural change (*e.g.*, increased consumption, increased sales of non-promotional goods due to complementarity effect). The valence of substitution effect depends on various factors, for example, whether the purchase of advertised good increases consumer surplus or satisfaction with respect to substituted product. Therefore, for construction of the accurate models of consumer welfare it is important to take these effects into consideration. However, decomposition of the total effect remains a serious issue[2]. Other methodological challenges include multi-collinearity, serial correlation between observations, measurement errors due to multi-channel nature of both purchasing behaviors and marketing campaigns, *etc.* Thus, rigorous research is required in the area of welfare analysis of advertising influence. Greater attention should be paid to the long run and indirect effects of advertising. I present an overview of the studies about such effects in the next section.

1.2.3.2 Effects of advertising on quality and satisfaction

Indirect and long run effects of advertising include changes in the reference prices (Winer, 1986; Kopalle et al., 1996), baseline sales (Kopalle et al., 1999), and brand franchise that may either undermine brand attitudes and loyalty or, contrariwise, reinforce brand positioning (Blattberg and Neslin, 1989). Moreover, in the long term, these effects may influence consumer satisfaction, expansion of product selection, and quality improvement due to enhanced competition, while in the short run they may result only in a "trivial and foolish" product differentiations (Borden, 1942b). Because product quality and satisfaction are important factors affecting consumers' welfare, I will focus on their relationship with advertising in greater detail.

The effects of advertising on consumer satisfaction according to Kaldor (1950) are oppositely-directed. On one hand, pleasure received from the purchasing of advertised brands increases satisfaction and shopping convenience, while on the other hand, it "leads to a constant tendency for actual satisfaction to fall short of expectation" (p. 8). Satisfaction in turn is closely related to the quality of goods.

Nelson (1974) finds positive correlation between advertising and quality, particularly for experience products. He attributes this relationship to the following

[2]See early works on decomposition of sales promotion effects: Gupta (1988); Chiang (1991); Dillon and Gupta (1996); Bucklin et al. (1998); Bell et al. (1999); Silva-Risso et al. (1999).

main effects: repeat-business, signaling-efficiency and quality-guarantee, and match-product-to-buyers.

According to the *repeat-business effect* customers satisfied with the high-quality goods of a certain brand are more likely to purchase the products of this brand again. Telser (1964) suggests the higher quality control as one of the factors increasing prices of advertised goods because a better quality control increases the marginal production cost. The model in Milgrom and Roberts (1986) predicts the separating equilibrium: when marginal costs are high, high-quality firms are better off when increase price and advertising intensity, while the situation is reversed for the low marginal cost situation.

The repeat-business effect is often observed together with the *signaling-efficiency effect*, which predicts that only efficient companies with low-priced and high-quality products are incentivized to advertise more heavily. Kihlstrom and Riordan (1984), for example, suppose that only high-quality firms with large mark-ups could afford the additional expenditures on advertising. Positive relationship between advertising and quality was further supported by Marquardt and McGann (1975); Rotfeld and Rotzoll (1976); Wiggins and Lane (1983); Kwoka (1984); Matthews et al. (1990); Bagwell and Ramey (1991); De Bijl (1997); Hertzendorf and Overgaard (2001); Fluet and Garella (2002), and in the empirical work of Archibald et al. (1983). In the analysis of Consumer Reports data Caves and Greene (1996) found positive relationship between quality and advertising only for innovative goods and goods that possess both experience and search qualities. Experimental studies of Kirmani and Wright (1989); Kirmani (1990); Homer (1995), and Kirmani (1997) showed the inverted-U relationship between advertising expenditures and consumer expectations about quality: while reasonable advertising intensity signals the producers' greater confidence about product quality, excessive volumes of advertising may imply the producers' "despair" to sell the low-quality good without aggressive promotion. Empirical evidence in Haas-Wilson (1986); Tellis and Fornell (1988); Horstmann and MacDonald (1994); Zhao (2000), and Orzach et al. (2002) further support the idea that efficient firms are more prone to inform consumers about high quality, while they have less incentive to advertise low-quality goods especially on the later stages of product life cycle. In contrast, Horstmann and Moorthy (2003) argue that advertising is more beneficial for the low-quality companies in low-demand states. Rogerson (1988) found that quality degradation due to price advertising is accompanied by the welfare improvement, since advertising in this case simply sorts the consumers by price segments.

The *quality-guarantee effect* is closely related to reputational argument. An established brand name is supposed to reassure even new customers about the quality of the products. Fogg-Meade (1901); Shaw (1912), and Marshall (1919) are among early supporters of the idea that large advertisers have bigger incentives to offer high-quality products than smaller companies. The notion of "quality-assuring price" that triggers the consumer quality perceptions was first discussed by Telser (1980) and Klein and Leffler (1981), then formally introduced by Shapiro (1983) and developed by Rogerson et al. (1986); Stiglitz (1989), *etc.* Braithwaite (1928), however, predicted only a modest quality-guarantee effect of advertising, because elevated reputation is not always translated into high quality and because consumers are limited in their capabilities to judge quality. Persuasive advertising advocates also largely support the negative social effects of advertising.

The *match-products-to-buyers effect* is less related to the product quality itself but rather to the value of correspondence between products and consumers' preferences. The matching role of advertising is discussed in Rosen (1978); Bagwell and Ramey (1993); Anand and Shachar (2005), *etc.* Theoretical models of Grossman and Shapiro (1984) examine the conditions (on the level of fixed costs and advertising technology) under which match-products-to-buyers effect creates the benefits for consumers and businesses. They suppose that in the case when an additional unit of advertising does not increase the number of informed consumers, the "wasteful" consumer-capture effect overrides the matching effect. Even when advertising purpose is purely informative, private benefits are higher than social gain. Lewis and Sappington (1994); Meurer and Stahl (1994); Johnson and Myatt (2003), and Lewis and Wang (2013), however, predict that social surplus is not monotonic in advertising because better matching can be accompanied by a reduction in sales. Anderson and Renault (2006) found that consumer surplus is positive when search costs are low and the value of match is high, otherwise, advertising message is required to signal expected search benefits to induce consumer to incur search cost.

Generally, the supporters of informative role of advertising tend to derive positive effects of advertising on sales, competition, product quality, and consumer satisfaction. The advocates of persuasive view on advertising, in contrast, are more inclined to emphasize the entry deterrence and adverse effects of ads on consumer surplus and prices. Although theoretical predictions and empirical evidence on causal relation between advertising and quality are mixed, a common trend, observed across various research studies, suggests that this relation is positive, at least under certain conditions. These conditions include the level of marginal costs of production, final products' prices and position in the life cycle, innovation, demand, consumers' expectations, *etc.*

1.2.4 Targeted advertising in traditional media

Targeting has been a reliable tool in marketing campaigns for decades. Marketing literature associates targeting primarily with market segmentation and reaching the consumers potentially interested in a product. Economic literature, in contrast, views targeting as instrument of consumers' reservation price elicitation. Therefore, from the marketing point of view, targeting helps to improve the marketing campaign's success by reaching the "right" audience without "wasting" advertising budget on those, who will not eventually purchase the product, and in parallel, to meet the consumers' interests and tastes. From the economic perspective, targeting helps to maximize revenue through extraction of consumer surplus using discriminating practices based on elicited reservation price. While advertising industry usually emphasizes benefits of targeting for consumers by offering more customized and relevant ads, it often suppresses the discussion about its economic consequences. Hence, in this section I will provide an overview of welfare implications of targeted advertising.

As a special promotional tool based on price discrimination coupons have been especially popular in 1980-s. Various models analyze the effects of market segmentation and the isolation of price-sensitive consumers through coupon targeting. For example, Bester and Petrakis (1996) view the welfare gain from receiving a coupon as a result of decreased brand-switching costs. Consumer surplus is negatively related to the transportation and couponing costs. Therefore, lower advertising cost leads to the producers' waste of money and, more often, to the brand-switching among consumers. Another model of couponing in Moraga-González and Petrakis (1999) reveals that consumer surplus is positively related to the degree of product differentiation and negatively correlated with the marginal cost of advertising.

Adams and Yellen (1977) show that socially desirable equilibrium can be achieved without distorting tastes and preferences and changing reservation prices even when advertising is costless:

> "If rich exhibit higher surplus on both brands than do poor people, then advertising may be used to make the rich disdain what the poor are urged to buy and covet what the poor cannot afford" (p. 444)

The classic "snob" and "keeping up with the Jones" effects support the above-mentioned idea (Veblen, 1899; Mitchell, 1937; Duesenberry et al., 1949; Galbraith, 1958; Baran and Sweezy, 1964). Adams and Yellen (1977) conclude that price-discriminating practices based on market segmentation are necessary for the increase in social welfare under Pareto-optimal solutions because they allow extraction of benchmark surplus generated by advertising from high-surplus consumers without changing the extraction of surplus from low-surplus consumers.

Hernández-García (1997) considers the effect of targeted advertising on social welfare to be the most harmful when consumers' product valuations are high. The increase in price for the low-demand consumers is relatively small and, therefore, leads to consumer and social welfare gains. However, increased efficiency due to targeting is more likely to exceed the increment of monopolistic market power.

A more recent model of Galeotti and Moraga-González (2003) suggests that informative targeted advertising increases prices in more expensive segment and decreases prices for the less expensive goods. However, authors do not derive the welfare implications. Esteban et al. (2007) also consider informative targeted advertising with price discrimination but for vertically differentiated rather than homogeneous products market. They find a stronger positive impact of targeting on aggregated consumer surplus than on producers' gain. They also emphasize a strong relation of targeting benefits to quality. Namely, the profit of a high-quality firm decreases due to targeting.

Iyer et al. (2005) predicts more extensive advertising for comparison-shopping segment when reservation prices increase, as it allows firms to extract more consumer surplus from the buyers with stronger product preferences. He also considers a positive relationship between targeted informative advertising and prices. Moreover, targeted advertising is expected to have a bigger effect on profits than targeted pricing. Similarly, Esteban et al. (2001, 2006) find positive relationship between targeted advertising and prices when consumers have high valuations for a product, while Bester and Petrakis (1996) show the opposite relation for low valuation buyers.

Hermalin and Katz (2006) draw attention to the importance of the level of targeting technology development: while perfect targeting is expected to increase efficiency, a moderate ability to target consumers reduces social welfare. Likewise, Johnson (2013) assumes a quasiconvex U-shaped utility function of online targeting, where consumers dislike imperfectly targeted ads but start to appreciate benefits once the technology reaches a certain degree of precision and sophistication.

Roy (2000) predicts a socially efficient equilibrium where all consumers have homothetic identical preferences, are captive and divided among mutually exclusive segments, in which advertising volume is minimized to a socially desirable level and companies appropriate all consumer surplus.

According to Esteban et al. (2001) consumer surplus and social welfare loss caused by the increased monopoly power due to targeting outweigh the gain from prevention of advertising wasting. Moreover, they predict the growth of market prices and media specialization beyond the socially optimal level.

In a later development of the model, Esteban et al. (2006) distinguishes between the high- and low-end quality, dependent on whether willingness-to-pay for a better quality is high or low. They find that the use of customer-directed advertising in the high-end case increases price and quality and is less likely to create a social welfare loss. The effect of upsurge in price and quality on the market power in this case is oppositely-directed. In contrast, the use of targeting in low-end case strengthens market power through a reduction of quality, regardless of the change in prices, creating, however, a social welfare loss. Finally, authors conclude that private and social incentives to use targeting are balanced, while quantity and quality supply incentives are misaligned. Further welfare implication analysis in Esteban and Hernández (2016) concludes that targeting is always beneficial for social welfare compared to the mass media advertising. Although low advertising prices and low specialization of targeting increase consumer surplus, and thus, are Pareto superior, they may have a downsizing effect on consumer surplus when specialization reaches a sufficiently high level. This has a particularly important implication in the context of digital advertising.

Persuasive targeted advertising causes an increase in prices and producers' profit by raising reservation price rather than by reducing search or transportation costs (Egli, 2015). Gnutzmann (2014) predicts the detrimental effect of dynamic behavior-based price discrimination (BBPD) on consumer surplus and social welfare, when switching costs exceed the price reduction arisen from a stronger competition. Esteves and Cerqueira (2014) show price growth in the first period followed by a subsequent drop in the second period causing negative effect on consumer welfare. Although the model considers product heterogeneity and imperfect information market, it makes several assumptions that are not likely to hold in the real world, *e.g.*, inability of consumers to buy a product without receiving an informative ad, and the guaranteed purchase by all informed consumers.

Chen and Pearcy (2010) view BBPD model from a perspective of time-dependent preferences: when correlation is strong, BBPD increases consumer surplus.

Thus, the effect of targeting on welfare depends on a number of factors, including product quality, consumer valuations and preferences, accuracy of targeting, and whether the ad is informative, price or non-price, *etc.* The conclusions of various schools of advertising are controversial. However, the impact of targeting in advertising is expected to be positive if it is not accompanied by the extraction of consumer surplus through price-discriminating practices, and decrease in quality. The effect of personalized advertising offers on consumers' welfare positively relates to the accuracy of an employed targeting technique.

So far I have been focused on the literature related to the traditional advertising channel. In the next section I move attention towards a more recent marketing tool - online advertising. I first describe the current infrastructure and state-of-the-art in that industry, then I analyze the models of targeting in online advertising; finally, I discuss how Internet advertising influences the well-being of the various elements of its ecosystem.

1.3 Advertising in digital media

Online advertising industry has complex and dynamically expanding infrastructure often referred to as advertising ecosystem. In a nutshell, there are *publishers* (websites that release content in the Internet, *e.g.*, news, search engines or video-sharing websites) and *advertising networks* that play a role of brokers connecting publishers with *advertisers* (firms that pay for the placement of their advertising content on the publishers' websites, *e.g.*, retailers or car producers). Finally, *audiences* are the users that visit websites and receive publishers' content together with the sponsored content. In this section I will discuss the influence of digital advertising on each of these advertising ecosystem's components. To start I first briefly explain how the programmatic ad buying (PAB) system works.

PAB is a fully automated system of individualized buying and selling of advertising inventory in real time. The assignment of ad impressions to advertising slots happens through an auction called real-time bidding (RTB). Typically, when user visits a website she prompts a bid request that goes from the publisher to an ad exchange. This bid contains a parcel of information about the user, *e.g.*, demographics, location, browsing history, *etc.* Tracking of the users' past activities in the Internet in general or on the seller's website specifically, usually by placing a cookie on their devices, gave rise to *behavioral targeting*, a special kind of targeting based not only on the demographic and socio-economic characteristics of the user, but also on his browsing history. Behavioral targeting made it possible for advertisers to identify the profile of a certain user before placing a bid and, therefore, to target ads more accurately. Being a platform facilitating the buying and selling of advertising inventory, ad exchange reveals the bid request to multiple ad networks and collects the advertisers' bids. The ad impression of the highest bidder is then served on the publishers' website. The whole process just described usually takes about 100 milliseconds from submitting the bid request to serving an ad. Therefore, RTB happens automatically, based on the parameters set by advertisers. These parameters include the upper boundary of bids, advertising campaign budget, user-related criteria of bidding, such as their demographics, conversion data, behavioral profiles, *etc*. Special technologies, based on the probabilistic models of user clicks and conversions depending on their profiles, help to determine in real time the value of individual impression. Advertisers use such technologies, called demand-side platforms (DSP), for organizing the workflow and reporting on ad-purchasing transactions. To manage the transactions with multiple advertising networks, publishers also use specific technologies, called supply-side platforms. Due to the two-faced nature of interactions, RTB is usually described as a two-sided market.

Internet advertising pricing models may be broadly divided into two large groups: 1) cost-per-impression (CPI); and 2) cost-per-action (CPA), also referred to as cost-per-acquisition, or cost-per-conversion. CPI model is derived from traditional advertising and was adopted at the early stages of online advertising development. According to CPI, advertiser pays for each impression viewed by a potential customer. As the volume of advertising is usually large, especially on the web, the cost is often defined for a thousand impressions, or cost-per-mille (CPM). However, it is not always possible to determine whether a customer has actually seen the ad. Therefore, CPA model emerges, where advertisers pay only for the ads for which an acquisition has occurred. This acquisition specified in the terms of agreement with publisher can be defined as click on the ad, contact request, registration, newsletter sign up, purchase, *etc*. For example, in the cost-per-click (CPC) model, the most popular form of CPA, advertisers pay only for the ad impressions that were clicked by the customers. CPA is better adapted to the measurement of advertising effectiveness than CPI, as it provides the metrics of users' interest and attention toward an ad due to enhanced ability to track users' behaviors and individual reactions to a certain ad.

Programmatic ad buying and behavioral targeting have revolutionized the way online advertising is traded now: it has became much easier to target a certain population precisely and at a low cost and to personalize the offers on the basis of the consumers' preferences inferred from the past online behaviors. Therefore, consumers are supposed to receive more relevant ads and save more on searching costs. Advertising industry report, based on a conjoint market research, claims that consumers absorb two thirds of the total Internet welfare, mostly through information- and communication-based consumer services (IAB, 2010). The distribution of consumer surplus is skewed with 60% of the gain captured by young affluent users living in big cities.

PAB seems to benefit the other side of the market as well. In 2014 it comprised one-fifth of the total digital advertising revenue, which was divided between ad-tech companies and publishers in proportion of 55/45 (IAB, 2015a). The use of automated buying systems claims to increase the efficiency and reliability of ad inventory management and to decrease costs. The decreased price of advertising, however, results in excessive volumes: ComScore reported that in total 5.3 trillion of display ads were served in 2012 (Morrissey, 2013).

However, white papers are often apt to subjectivity. Therefore, in the next section I will focus on scientific sources to scratch the surface of a modern dilemma on who eventually gains and who bears the burden of online advertising deployment? I will summarize both the theoretical predictions and empirical evidence on the effects of digital advertising first on advertisers and industry as a whole, and then on consumers.

1.3.1 Theoretical predictions on the impact of digital advertising on consumer surplus and net welfare

Bergemann and Bonatti (2011) provide a comparative welfare analysis of advertising in traditional and digital media. They acknowledge positive relation between targeting and social welfare due to improved matching, but point out that the effect of targeting on producers' revenue depends on the size if the business: small and large companies gain from targeting and medium size firms may experience losses on the early stages of targeting employment.

Informative view of advertising emphasizes the positive effect of ads on reduction of search costs, which is especially beneficial for consumers with high time costs or when alternative methods of acquiring information are inefficient (Verma, 1980; Laband, 1986; Sauer and Leffler, 1990). Malheiros et al. (2012) see an additional benefit of ad offers' personalization on the reduction of irrelevant ads and prices of the products and services, together with the granted free access to the websites' content.

Ehrlich and Fisher (1982) view advertising incorporated in a broader theory of selling efforts and thus being interdependent on the decisions about alternative informational services, such as trade shows, customer services or store displays, their prices and welfare impact. They found an empirical evidence of detrimental effect of advertising on time cost, which, in turn, is derivative of search efforts. Goolsbee and Klenow (2006) also directly include the opportunity cost of time into their model of Internet users' surplus calculations.

Stivers and Tremblay (2005) consider the strong positive effect of informative advertising for the search goods on consumer surplus and social welfare and negative effect in the case of persuasive advertising as it does not affect the consumers' search costs. Instead of looking on advertising from only one angle, Hoffmann et al. (2014) consider ads as informative and persuasive simultaneously. In this condition behavioral targeting increases consumer welfare if they are aware about data collection practices (*e.g.*, through consent mechanism) and when firms are not involved in price discrimination. Intense competition among firms protects unwary consumers from being exploited.

Johnson (2013) finds that the reduction of advertising intensity leads to the social benefits by making both consumer and producer better off only if cost/benefit ratio for the buyers exceeds such ratio for the sellers. While targeting is lucrative for all firms, it is more beneficial for the niche firms that are able to reach “the long tail of the Internet” and match their offers to the niche consumers, making them better off as well. However, on the general population of consumers, the proliferation of targeting has two oppositely directed effects: increased relevance of ads and increased advertising volume. Therefore, consumers, subject to advertising avoidance, may react on excessive advertising intensity with the ad-blocking activities. Such blocking causes the loss of firms' surplus but benefits all consumers, first, by reducing the advertising volume, and second, by removing irrelevant ads from circulation.

De Corniere and De Nijs (2016) include the privacy component and ad platform revenue in their welfare analysis. They found that the disclosure of personal information increases net welfare and leaves a bigger portion of profit to the winning bidder, which otherwise would be completely absorbed by the platform. Better preference matching may outweigh consumers' welfare loss from increased prices and, therefore, firms have an incentive to avoid personalized pricing.

Advertising (especially in the case of repeated exposure) increases the probability of the product to be included in the consideration set (Shapiro et al., 1997; Mehta et al., 2003; Terui et al., 2011). If targeted offer has high-value for consumer, then according to the consideration set formation model (Hauser and Wernerfelt, 1990) she would be discouraged from continuous exploration and evaluation of other options. Therefore, although from the firms' perspective, personalization leads to a higher level of competition due to the low differentiation (Zhang, 2011), from the users' perspective, targeted advertising can inhibit exploration in goal-oriented search (Fong, 2012). That has a particularly negative effect on sales for the products about which consumers have low awareness or familiarity. It violates the prescription of a normative theory to start exploration from the higher variance options (Weitzman, 1979) and therefore, may be sub-optimal for the consumer welfare, especially in the long run.

In their game theoretic model, Xu et al. (2012) argue that although organic listings may reduce firms' revenues in the short run, they improve social welfare and long-term business prosperity due to increase in consumer surplus, sales diversity, consumer base growth, and adjustment of the bidding outcome.

Anderson et al. (2007); Anderson and De Palma (2013) predict a positive effect of ad price increase on consumers' surplus and firms' revenues due to crowding out the low-quality messages and increasing the probability of remaining ads to be examined.

Bruestle (2014) derives a model of strategic ad platform inefficiency, where interests of advertisers and ad-tech companies are misaligned to a point where ad seller even has an incentive to show ads to the “wrong” consumers, which are less likely to buy the advertised product. In the pay-per-click pricing model, in which advertiser pays to advertising platform for an ad only if a user has clicked on it, ad seller is trying to maximize the number of clicks. By showing the ad to the low-valuation consumers, who are not expected to make a purchase, ad platform induces the reduction in product price that in turn makes consumers more likely to click on the ad of such product, increasing the advertising industry revenue, but not the firms' sales. Bruestle (2014) shows that take-it-or-leave-it pricing model in which ad platform influences ad price rather than number of clicks leads to a more efficient targeting. However, the models proposed by Bruestle (2014) lack the empirical evidence.

For the similar reason advertising agency is not incentivized to eliminate the ad inventory for a certain product from the circuit of exposures to a particular user, even after this user has already bought a product. For example, imagine a user searching for a new smartphone. This user is tagged as "interested in buying a smartphone". Therefore, the advertising of smartphones may be considered as relevant for this user, satisfying the idea of both informative and persuasive schools, because companies deliver the information about their products that may satisfy the detected need and, at the same moment, try to persuade the user to buy a product of a particular brand. After the consumer has bought the smartphone, ad platform is often informed about this event because it is tracking consumers' online activities, and technically is able to remove the tag of "interest in buying a smartphone" from this particular user. However, in reality it does not remove the tag in order to preserve the revenue flow. This action violates the primary role of advertising to match sellers to buyers. Therefore, such actions may be considered as examples of strategic ad platform inefficiency.

Thus, targeting is expected to have positive effect on the net and consumer welfare if it improves buyer-product matching and reduces search and transportation costs. Excessive volumes of advertising, non-transparent and discriminating practices that often accompany targeting deteriorate the net and consumer welfare. As an additional spillover targeting is found to inhibit consumers' exploration activities that may be sub-optimal in the long run. In the next section I turn to the empirical evidence of the influence of digital advertising in general, and targeting in particular, on the industry and consumers.

1.3.2 Empirical evidence on the impact of digital advertising

1.3.2.1 The effects of digital advertising on industry

Together with artificial intelligence technologies the programmatic advertising facilitates the use of behavioral data generated by numerous online tracking systems for fine-grained targeting of advertising offers to the particular audiences. Search ads (*i.e.* sponsored links on the search engine result pages) increase the number of websites' visits by 15%, and sales by 48% (Sahni, 2015). Online display ads, which appear on the publishers' websites in a form of banners, pop-up windows, videos, *etc.*, increase site visits by 16% and conversion rates by 8% (Johnson et al., 2015b). 18% of online advertising revenue accounts for behavioral targeting (IAB, 2010). On average, targeting increases CTR by 65%, brand search ad effectiveness by 40% (Farahat and Bailey, 2012), and consumer welfare by 60% (Jeziorski and Segal, 2015). Counterfactual experiments in Yang and Ghose (2010) show increase in click-through-rates (CTR) (6.6% *vs.* 2.77%) and in conversion rate (5.71% *vs.* 1.67%) for paid search results compared to the organic listings. This is translated into 3.1 times growth of the advertiser's revenue. The willingness to pay the price for the targeted ads is 2.68 times higher than the cost of run-of-network advertising, suggesting the generally positive value of targeting for advertisers (Beales, 2010). Aziz and Telang (2016) analyze the bid requests and subsequent purchasing data and find that targeting is effective, and that some privacy-intrusive temporal information (*e.g.*, about past visits of the advertiser's website) improves advertising effectiveness by 30% with regard to random targeting. Johnson et al. (2016) find that retargeting increases website visits by 17%, the number of transactions by 12%, and sales by 11%.

However, other empirical studies conclude that the effect of advertising can be often overestimated. Some big companies, *e.g.*, Procter & Gamble Co., publicly admit that targeted advertising campaign in Facebook is less effective than general advertising with broader audience reach (Terlep and Seetharaman, 2016). I further support the discussion of the factors that may impede the actual effectiveness of digital advertising and targeting with empirical findings from the literature.

One of the reasons, why industry-stated effectiveness rates may be exaggerated, is related to the methodological mistakes. For example, once controlled for category and brand interest, consumers do not respond to targeted ads differently from untargeted users (Farahat and Bailey, 2012). Another methodological issue is a self-selection bias: people with higher purchase intent, and therefore, higher probability to convert, are more likely to click on the ad or paid search result. Indeed, Aziz and Telang (2016) show that targeted advertising is positively correlated with the users' baseline purchase probability.

Based on the self-perception theory (Bem, 1972), Summers et al. (2016) study social labeling effect of behaviorally targeted advertising and concludes that the positive influence of such personalized offers on purchasing intent is mediated by the relevance of implied label, *i.e.* by the accurate prediction of the close connection between social label and the consumers' past behavior.

The timing also matters. Lambrecht and Tucker (2013) show that targeting may be less effective on the early stages of purchasing process. Empirical study in Yan et al. (2009) demonstrates that the value of behavioral information decreases over time: targeting based on one-day old search history causes a 670% improvement in CTR, whereas the information about one-week old search queries increases CTR only by 300%.

The research conducted by Google (2014) finds that 56.1% of served impressions are not even viewed by the users, mostly because of the page position, ad size, and device screen settings. The Interactive Advertising Bureau called the advertising industry to recognize and transit from 2015 to the new transaction principles aiming to separate the served impressions into measured and non-measured, and to account for the 70% viewability threshold for the latter group. Interestingly, this requirement demands publishers to deliver "all make-goods <. . . > in the form of additional viewable impressions, not cash" (IAB, 2015b, p. 3). In other words, advertisers' expenses spent on the ads that eventually were not viewed are not going to be reimbursed, but converted into additional bundle of viewable impressions. It means that because of its detrimental effect on advertising industry's revenues, no question is arisen about reduction of the gross ad volume, which could have had a positive impact on consumers' attention. Instead, advertising industry offers to increase advertising intensity by providing the second chance to deliver an ad that was not viewed, this time "for free".

Nevertheless, even delivered and viewable ads are not necessarily noticed by consumers. The phenomenon of "banner blindness", when users avoid looking at banner ads, was first introduced by Benway (1998). Numerous studies used eye-tracking technologies to investigate the phenomenon and found affirmative evidence (Drèze and Hussherr, 2003; Lapa, 2007; Chatterjee, 2008; Hervet et al., 2011; Owens et al., 2011; Resnick and Albert, 2014).

The tiny fraction of viewable and seen ads still does not necessarily translate into action. CTR has been shown as imprecise measurement of the ad effectiveness, because only a little proportion of clicks on banner ads converts into purchase (Chatterjee et al., 2003; Moe and Fader, 2004), while nonetheless may contribute to the enforcement of brand positioning, awareness, and loyalty. Pretarget and ComScore analysis of 263 million ad impressions collected over 9 months across 18 advertisers from various industries revealed that Pearson correlation between gross impressions and conversion is only 0.17, providing the evidence of the low efficiency of the "spray and pray" approach (ComScore, 2012). Moreover, clicks on ads are often accidental (Felix, 2012) or represent shortcuts for faster access to intended websites (Blake et al., 2015).

Another source of error in the ad accountability is the lack of transparency of advertising system to advertisers themselves. Although ad-selling companies provide frequent reports and analytic tools to monitor the advertising campaigns' performance, advertisers, in fact, do not have control over reliability of this information. Neither do they know whether a particular user was targeted correctly nor whether the impression was served to the specified audience. Google AdSense terms and conditions state that advertising payments are calculated on the basis of AdSense's accounting, not on the advertisers' traffic analysis. The very process of RTB auctions remains opaque. For example, the platform can adjust the payments by any amount "arising from invalid activity, as determined by Google in its sole discretion" (Google, 2016).

Finally, the impact of various fraudulent attacks on effectiveness metrics has been hotly debated over the last decade (Mungamuru and Weis, 2008; Stone-Gross et al., 2011; Alrwais et al., 2012; Mladenow et al., 2015). These attacks include activities of hired clickers, remotely controlled compromised computers (*e.g.*, clickbots), misdirected human clicks (so called "ghost clicks"), keyword or impression stuffing, *etc.* The Association of National Advertisers predicted the $7.2 billion loss in 2016 due to fraudulent ad impressions (ANA, 2015). Zain (2015) reports that, on average, 50% of impressions are served to bots rather than to human in-target audience. However, in 79% of campaigns only 1% of ads are served to non-human traffic (Lella and Lipsman, 2015). This means that the loss is not equally distributed among advertisers, but rather a small number of campaigns experience a large proportion of loss being heavily compromised by fraudulent attacks. If the victims of such attacks have a common profile, for example of the small local businesses, the created misbalance may hurt competition and shift the equilibrium. What are the campaigns typically subjected to attacks and what is the effect on market structure and net welfare are the relevant questions for future research, both theory- and evidence-based.

Ohm (2013) heavily criticizes the popular and often cited studies that emphasize the benefits of behavioral targeting (*e.g.*, Goldfarb and Tucker, 2011b; Beales and Eisenach, 2014) for being "based almost entirely on dubious and unstated assumptions" (p. 11), for using self-reported answers instead of solid real behavioral observations, and for methodological and statistical analysis weaknesses (such as large variance, outliers, collinearity, and low model fit). Moreover, he draws attention to the fact that some studies (for instance, Beales, 2010; Deighton and Quelch, 2009) are funded by marketing associations, and, therefore, might be subject to conflict of interests. Finally, he notes that such studies seem to deliberately avoid comparison of behavioral and contextual advertising effectiveness, "cherry-picking" the cases that would qualify for research purposes.

Strandburg (2013) argues that the main reason of contradictive evidence on the supremacy of behavioral versus contextual advertising is related to the difficulty of accurate effectiveness assessment. The results of 25 field experiments with large U.S. retailers conducted by Lewis and Rao (2014) further support the statistically small advertising effect and discuss such methodological issues as selection bias, noise, and large confidence interval on return on investment that impede the analysis of advertising campaign performance. They also point out that randomized control trials with over 10 million users would improve the reliability of statistical results but limit feasibility of such approach only to the largest companies.

Moreover, the current structure of advertising eco-system raises an antitrust issue. In Q4 2015, 75% of digital advertising revenues were concentrated within top-10 advertising selling companies (IAB, 2016). Multiple functions, services, and affiliations of online advertising value chain, such as publishers, ad networks, ad exchanges, are often consolidated and controlled by a single leadership. In other words, different players in the wide advertising eco-system are part of few large companies. The most prominent example of such conglomerates is Alphabet Inc. (informally refereed to as Google) that among other subsidiaries and services includes advertising networks AdSense (advertising sales channel and content targeting) and AdWords (media buying channel), AdMob (mobile advertising), DoubleClick (bid manager), Invite Media (display advertising and exchange bidding), and Google Analytics (web traffic analytics). High concentration in the industry may be a perturbing signal of potential distortion of the market equilibrium in favor of monopolistic stakeholders under a secure protection of legal departments, especially in the case of further relentless upholding of their interests without an appropriate attention to the more disaggregated and unprotected parties, among which consumers are often pushed to the very background.

On the other hand, small companies often experience difficulties with compliance with the legislative regulation, which is becoming more and more strict nowadays, due to the lack or large costs of legal advice and limited budget for testing and deployment of privacy and security protective solutions. With this regard large companies can offer a higher level of privacy control and protection, also because their established reputation is at stake. The consequences of potential data breach may cost more than expected revenue gain due to the introduction of a privacy-invasive practice. Finally, consolidated systems have a greater market power and are able to offer better deal conditions leaving more profit share to the publishers rather than dividing it between numerous ad-tech companies. However, such effect will hold only in case of the presence of market competition among advertising agencies, not at the monopolistic market. In sum, consolidation processes in the advertising market has a potential for improving the security and control over the advertising quality, ensuring privacy compliance, and balancing the revenue allocation between ad-tech industry and publishers (in the absence of monopoly), while increasing market concentration, ubiquitous control, and expanding its power to a bigger number of aspects of human lives, such as political opinions, knowledge, health management, *etc.*

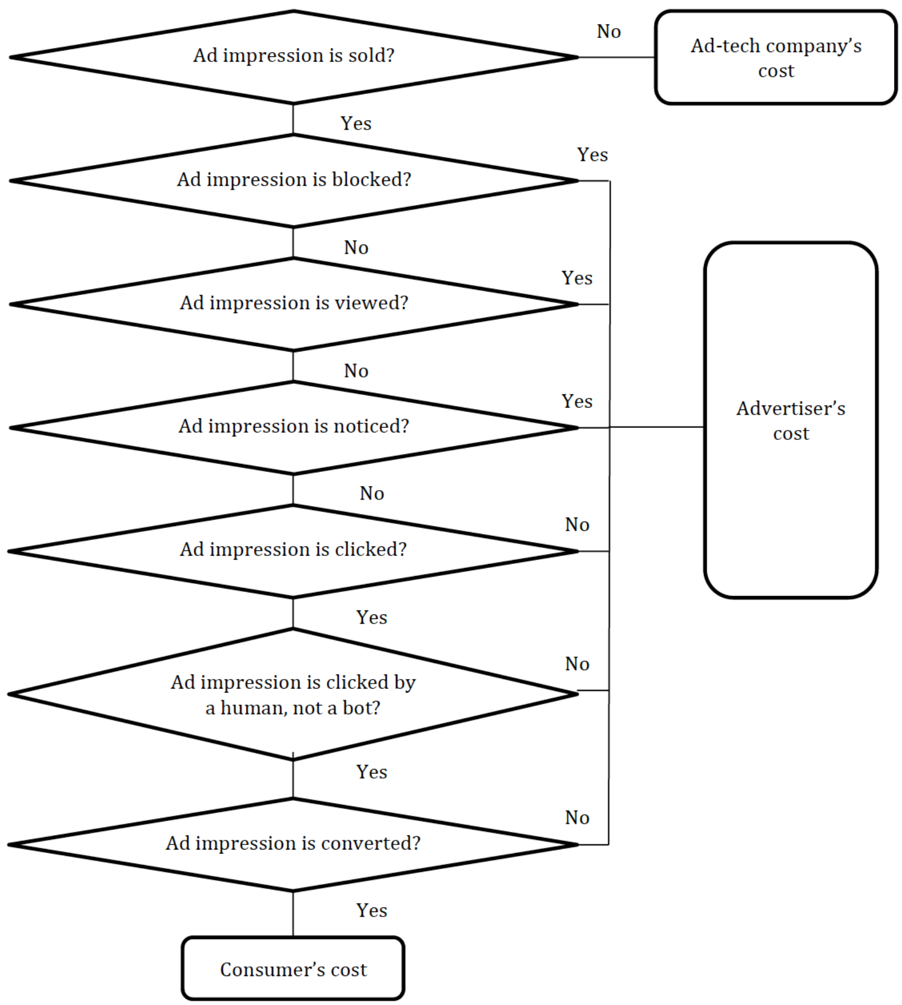
Thus, the effects of online advertising in fact appear to be more opaque and complicated than optimistic and enticing affirmations of advertising industry to boost marketing campaigns effectiveness and revenues claim. Fig. 1.1 summarizes the thorny path that each ad impression is supposed to overcome in order to reach the promised success. The main reason why advertisers continue the walk across this minefield is that the cost of failure to deliver an online ad impression successfully is extremely low, so they untiringly pour fire of excessive and intrusive advertising on consumers' heads. Is it a shortsighted strategy in the long run?

In this section I have summarized the effects of online advertising primarily on the advertisers' and ad networks' revenues found in the theoretical and empirical research studies as well as in the industry reports. In the next section I focus on the effect of digital advertising on the end consumers.

1.3.2.2 The effects of digital advertising on consumers

Although theoretical models predict the reduction of search and transportation costs, free access to the websites' content, and increased seller-buyer matching due to targeted advertising, the collection of vast user data, sometimes without even clear idea about intended use and means of confidentiality protection, poses a threat to information privacy and security, resulting in users' discomfort, stress, and other negative psychological effects. Moreover, abundance of the advertising content leads to a serious information overload, hindering the cognitive abilities. Finally, targeted advertising sometimes creates the market inefficiencies and negative economic consequences for consumer welfare. I now will discuss each of these effects in detail.

Figure 1.1: Decision tree for assignment of the cost of online ad impression delivery under the pay-per-impression model



Psychological effects Two-thirds of American users are not supportive of behavioral advertising (Turow et al., 2009; Morales, 2010), one third is uncomfortable (Hastak and Culnan, 2010), and 67% of European users expressed concern about lack of control over their information revealed online (Eurobarometer, 2015). Although 74% of the interview respondents say that they would prefer targeted ads to non-targeted, over 60% find targeted ads harmful, annoying or too persuasive (Melicher et al., 2015). Other surveys show even lower acceptance of behavioral advertising (see Turow et al., 2009; TRUSTe, 2011). While industry claims advertising to be a necessary condition for preserving the "free" status of the prevalent proportion of the Internet content, 91% of U.S. respondents disagree that it is fair to exchange the collection of personal information for a discount (Turow et al., 2015).

Melicher et al. (2015) find that the level of users' comfort with tracking technologies heavily depends on contextual factors such as type of data being tracked, frequency of website visits, and whether the tracker is a first- or third-party entity. Very often tracking technologies are deployed against particularly assailable population, such as children, people with health problems or in difficult situation in life (Angwin, 2010; CDD, 2012).

People are reluctant to share sensitive data (Leon et al., 2013), especially when they perceive it as irrelevant for advertising or may be misused (Leon et al., 2015). Imperfection of marketing data, in turn, accounts for imprecise targeting (Van Zandt, 2004). Ill-customized ads lead to the consumers' discomfort (Malheiros et al., 2012), irritation (Thota and Biswas, 2009), reactance (Clee and Wicklund, 1980; Edwards et al., 2002; Fitzsimons and Lehmann, 2004; Ying et al., 2009), and sometimes even to embarrassment (Agarwal et al., 2013; Melicher et al., 2015). Increased attention to an ad due to the application of intrusive personalization techniques, for example, using consumer's photo or name, is offset by amplified users' discomfort (Malheiros et al., 2012) that in turn can affect purchase intention (Van Doorn and Hoekstra, 2013). However, the justification of personalization deployment and high perceived positive product utility considerably offset reactance (White et al., 2008).

Information overload Average U.S. Internet user is exposed to 1,707 banner ads per month. Millennials (24-35 year old) are served even more, over 2,094 banner ads per month (Goo, 2014). In the model of network of targeted communication Van Zandt (2004) acknowledges that although information from a single sender may be optimal, the total amount of information sent to a single receiver may be overloading due to limited attention abilities. Therefore, the average value of such information decreases. Moreover, the perception of interruption, advertising content incongruence with the task, and cognitive intensity are recognized antecedents of perceived intrusiveness and subsequent ad avoidance (Edwards et al., 2002). The empirical evidence proves that Americans are most likely to ignore online banner ads (73%), followed by the social media ads (62%), and search engine ads (59%). Millenials are likely to ignore digital ads more than traditional ones (Morrissey, 2013).

Although many studies confirm that generally users do not pay attention to banner ads, Burke et al. (2005) show that banner blindness comes with a cost for users by hindering visual search and augmenting the perceived cognitive workload.

Since a seminal work on "Information processing models of cognition" (Simon, 1979), a number of studies have investigated the consequences of informational overload (see Edmunds and Morris (2000) and interdisciplinary review of Eppler and Mengis (2004)). Among the main effects and symptoms of information overabundance researchers highlight cognitive tension and stress, decreased accuracy of decisions (Malhotra, 1982; Schick et al., 1990; Hwang and Lin, 1999) and greater error rate (Sparrow, 1999), increased time required to reach a decision (Jacoby, 1984; Hiltz and Turoff, 1985), hurdles in identifying relevant information (Jacoby, 1977) and reduced ability to use this information for decision-making, often referred to as "paralysis of analysis" (Bawden, 2001), high selectivity and the neglect of a big portion of information (Hiltz and Turoff, 1985; Herbig and Kramer, 1994; Sparrow, 1999; Bawden, 2001), limited search directions (Cook, 1993) and loss of differentiation (Schneider, 1987), negative effects on satisfaction (Jacoby, 1984; Jones, 1997), and overconfidence with respect to security because of the uncertainty reduction (O'Reilly, 1980; Jacoby, 1984; Meyer, 1998). In the online experiment with over 1200 participants, Goldstein et al. (2013) find that when exposed to attention-captive ads, subjects perform an e-mail classification task with less accuracy than subjects in "good ads" or "no ads" conditions. Authors also attempt to measure the cost of annoying ads as compensative wage differential, and estimate the premium for low-quality ads to be \$1.53 click-per-mille (CPM) with respect to no ads, and \$1.15 CPM – with respect to non-intrusive high-quality ads.

Market inefficiency Apart from psychological discomfort and privacy issues, targeting can cause the real economic harm to consumers, for example, through the price or offer discrimination (Angwin, 2010; Mattioli, 2012; Datta et al., 2015), price steering (Hannak et al., 2014), *etc.* Not all consumers are aware of such practices.

Ohm (2013) states that:

> "Almost nobody can ever be persuaded by online ads. $<\ldots>$ Ads simply do not work on the vast majority of people, and the only reason they are worth outlay is because they are so cheap." (p. 30)

He further underlines the big potential of subliminal effect of advertising and warns that subconscious thinking is involved in 95% of buying decisions (Zaltman, 2003).

Hoofnagle and Whittington (2014) and Strandburg (2012) analyze the market inefficiencies of online behavioral advertising deployment from the point of view of transaction cost economics and traditional economics market failure approach. Based on their discussion, Ohm (2013) summarizes the reasons of such inefficiencies as information asymmetry due to the lack of transparency, anticompetitive and entry-detrimental effects arisen from networking externalities, and consumers' failure of risk and cost assessment due to bounded rationality.

Diversity Empirical evidence suggest that targeted and personalized offers, recommendations, and comparison matrices decrease the customer search activities (Häubl and Trifts, 2000; Tam and Ho, 2006; Fong, 2012), and therefore, reduce the customer-level sales diversity (Xu et al., 2012), while increasing the probability of finding and purchasing the niche products (Brynjolfsson et al., 2011). As a solution, Rutz and Bucklin (2011) suggest the consumers to start from generic search of the products and information, gradually increasing the specificity through the filtering functions or brand search.

In this section I showed that online advertising, especially behaviorally targeted, induces the high level of concerns, psychological discomfort, and real economic harm among users. As the result of reactance, consumers start to take vigorous actions in protecting their interests, *e.g.*, blocking ads, using encryption and other privacy-enhancing technologies. The deployment of such tools is disturbing both advertisers and ad-selling companies and is nudging them towards the further sophistication of marketing techniques in order to overcome the burdens imposed by users. The next section summarizes research about privacy-enhancing technologies and its role in modern online environment.

1.4 What's next?

In the previous sections I provided an overview of the theories, models and predictions of the various schools of thoughts on the role and impact of advertising in traditional media that has been developed in the past. I then summarized the results of empirical studies, including lab and field experiments, surveys, and econometric analyses, carried out in the last two decades in the field of economics of advertising, with a specific focus on online advertising and targeting. In the present section I expand the argument to the topics emerged in the most recent times and examine the ways in which users react to the development of online targeted advertising and provide an overview of the technological solutions aimed to help consumers to exert control over their online privacy. I then analyze the potential effects of the deployment of privacy-enhancing technologies in general, and the ad-blocking tools in particular, through the lens of theoretical predictions and empirical evidence on the advertising restrictions. Finally, I discuss the potential future of online advertising and the alternative routes and strategies that advertising industry may adopt in response to consumers' reactions, attitudes, behaviors, and needs.

1.4.1 Privacy-enhancing technologies

By privacy-enhancing technologies (PETs) I broadly refer to a set of tools, services, and protocols that can be deployed to protect individuals' privacy through a variety of strategies, *e.g.*, plugins, browser extensions, mobile applications, that block ads, manage cookies, prevent third-party tracking, *etc.*

For the purposes of this chapter, I distinguish and focus on two functionalities related to the protection from online advertising and targeting that could be achieved using PETs: ad-blocking and tracking prevention. Note however, that this distinction is contingent, because many of the tools that prevent websites from tracking of the users, are also able to block ads.

Survey results in Chanchary and Chiasson (2015) show that users find tracking prevention tools (TPT) to be more useful than ad blocking tools (ABT) (55% *vs.* 37%) and that 72% of them would prefer TPT to ABT. Similarly, in a 2,912-participant online study Leon et al. (2013) find that willingness-to-pay for TPT is higher than for ABT ($3 *vs.* $2.25).

The number of global monthly active users of various types of ad-blocking software achieved 198 million in 2015, representing a 41% growth over the previous year and a $21 billion loss in revenues (PageFair, 2015).

However, the way ad blocking works now does not seem to allocate the liability for losses among advertising ecosystem elements equally. An advertising slot is put up for auction, using RTB systems various advertisers made a bid, the ad inventory has been eventually sold, ad-tech companies have appropriated the profit, but the ad exposure did never happen if the user enabled the ad-blocking software. Therefore, the employment of ad blocking usually backfires to the advertisers and publishers but not to the ad-sellers.

In response to development of PETs aimed to protect users, another body of technological solutions is emerging from the advertisers' side. For instance, a tool called ClarityRay[3] or a free JavaScript program offered by PageFair monitor ad blocking on the websites (Ryan, 2016). When publisher detects the ad-blocking activities it can explicitly ask users to disable ad-blocker or to whitelist the website in order to access its content, like it is doing now forbes.com, for example. The cost of deployment of such technologies again largely rests on the shoulders of publishers, and the end consumers will inevitably incur the part of these costs.

Interestingly, once the user allows a website to show ads, this website is likely to remain whitelisted for a long period of time, even when the conditions of the initial "contract" change, because users often tend not to revise their decisions due to status quo bias. Some companies strategically exploit such behavioral biases, for example by providing the limited default ad-blocking and anti-tracking functionalities, and leaving the manual configuration of the setting for the customers. As a result, 80% of users stick to the default settings that provide the mediocre protection and only 15% of AdBlock Plus users set up the plugin in a way that ensures a good level of protection from advertising content and online tracking (Wills and Uzunoglu, 2016). Moreover, some websites do not ask to disable the ad blocker right after detecting it. Instead, they first engage user in reading an article, and then request whitelisting in exchange for the access to full text. In this case user may feel too involved in reading an

[3]https://clarityray.com

article and overestimate the benefit of immediate discovering of the rest of the content over the more uncertain benefits of keeping the ad-blocking tool on. Therefore, strategic exploitation of present bias may lead people to make the myopic decisions that in a long run could harm their privacy.

Some companies (*e.g.*, Admiral, Secret Media) go even further and create anti-ad-blockers that "reinsert" ads and promotional videos into the websites where they would be otherwise blocked. Practically, they make ads undetectable by the most ad-blockers (Terlep and Seetharaman, 2016). Similarly, Facebook announced in August 2016 an intention to make its ads more difficult to detect and force the ad exposure on users of ad-blocking software. Vice president of advertising and business platform in Facebook, Andrew Bosworth, agrees that forced exposure to online ads of the users, who are actively trying to avoid them, may increase the level of irritation among them. However, he prioritizes the ad revenue matters over potential harm of customer experience. He also believes that Facebook's efforts to ensure relevance and appropriateness of ad volume and to give control over the type of ads the users see are sufficient to keep the "ad load" in a "good zone" (Marshall, 2016). Nevertheless, the criteria defining relevance, appropriateness, and "good zone" boundaries are opaque and in the whole discretion of the company.

The outcome of this ongoing conflict of interests, allocation of the surplus generated by advertising, and the role of PETs in the "arms race" is unknown, or at least uncertain, by now. In order to understand the effect of ad blocking on consumers' welfare one need to understand how the elimination of advertising influences market equilibrium. Therefore, in the next section we investigate the existing literature about models and empirical evidence (primarily from the field and natural experiments) on the impact of advertising restrictions.

1.4.2 Advertising restrictions

Although the ad-blocking technological solutions are quite novel and specific for the online industry, the idea of restricting advertising intensity in general is not new. Since early 1970-s the researchers were interested in the examination of the economic impact of constraints introduced to the traditional advertising industry and developed a number of theoretical models, while the state regulators' tests of the various advertising restriction policies and bans provided a great opportunity to collect the empirical data for validation of the models through the natural and field experiments. In order to understand and make the prediction about the influence of modern ad-blocking tools on consumers' welfare and market equilibrium I start from reviewing the academic literature on theoretical models and empirical evidence of the impact of advertising restricting policies.

1.4.2.1 Theoretical predictions on the effects of advertising restrictions

A model in Adams and Yellen (1977) shows that a ban on advertising may reduce the producers' costs by eliminating advertising expenditures, increase the monopolists' benefits. The effect on social welfare, however, depends on whether the prohibition of advertising creates or eliminates the gap between equilibrium and socially optimal supply.

Milgrom and Roberts (1986) find the Pareto deterioration effect of advertising ban, where the only remaining opportunity for a firm to signal the product quality is through the price. Therefore, the consumers are worse off, because they acquire the same information but for a higher price[4]. Kwoka (1984) also predicts the detrimental effect of advertising restrictions on quality.

Bester and Petrakis (1995) link the welfare effect of ban on advertising to the elasticity of demand: the welfare gain is expected in elastic demand market, while in inelastic market, advertising and consumer transportation costs exceed social benefit from the augmented output.

Repetition of advertising messages increases brand awareness, recall, and chance to attract attention (Drèze, 1999; Pieters et al., 2002; Chatterjee et al., 2003; Nottorf, 2014). Therefore, when the price of advertising message is low, advertising intensity can exceed the socially optimal level. As the instrument of regulation of advertising clutter, alternative to the complete ban, Anderson and De Palma (2013) consider a cap on the number of advertising messages sent to each consumer. The impact of such regulated cap depends on the outcome of counteraction between the two opposite effects: the reduced congestion and the limited ability of the higher-profit firms to stand out.

Thus, the theoretical models predict a negative effect of advertising restrictions on quality, while its influence on welfare depends on demand elasticity, volume, and advertising role. Next section summarizes the results from empirical research about restrictions on advertising.

1.4.2.2 Empirical evidence on the effects of advertising restrictions

The natural experiments based on the U.S. state-level differences in legal regime of industry advertising conducted by Benham (1972); Cady (1976); Maurizi and Kelly (1978); Feldman and Begun (1978, 1980); Kwoka (1984); Becker and Murphy (1993) and a large-scale survey in Schroeter et al. (1987) have become the classic examples of the impact of regulations applied to informative advertising. The highest prices were observed in the states where advertising was banned completely, slightly higher in the states with only non-price advertising, and the lowest - in the states with no advertising restrictions. As the informative school of advertising suggests, legal restrictions hinder the free flow of information creating the entry-deterrence effects for the low-price firms (Benham and Benham, 1975; FTC, 1980; Haas-Wilson, 1986). Glazer (1981) study of the impact of two-month newspaper strike on the supermarket food prices, and the longitudinal studies on restrictions of the price advertising in the liquor industry in Milyo and Waldfogel (1999) and Luksetich and Lofgreen (1976) support the conclusion about price increase after the introduction of advertising limitations. However, as Benham (1972) points out, greater attention should be paid to the

[4]His model, however, analyses only market of the new experience goods rather than established brands.

possible endogeneity problem and to the disentangling of the possible confounding factors that may affect both, the retail prices and advertising restrictions, *e.g.*, formation of the alliances among advertisers.

While Farr et al. (2001) agree that advertising restrictions increase prices, their welfare analysis of U.S. cigarette industry suggests that elimination of such restrictions increases social welfare only if the external costs of smoking are low. The degree of consumer surplus reduction following the advertising restrictions depends on the nature of such advertising: the effect is the smallest when advertising is purely persuasive, moderate when it is informative, and the strongest when ads are mostly image-creating.

Using data from American brewery industry Tremblay and Tremblay (1995) found that the reduction of advertising expenditures below equilibrium level causes price increase, while the complete advertising prohibition, in contrast, decreases prices. Anderson et al. (2007) reach the similar conclusion: allowing users to opt-out from receiving messages is socially preferable to the complete advertising ban, while whether opt-out practices would outperform open access is less clear and depends on the surplus gain and total number of opt-outs.

In the context of online advertising, Johnson (2013) considers three online tracking restrictions policies: opt-out and opt-in plans that forbid or permit firms to track users by default, and a tracking ban that prohibits user tracking under any circumstances. Empirical analysis of the vast online ad-auction data suggests that under those conditions online publishers' profits drop by 3.9%, 34.6%, and 38.5%, that can be translated into \$52, \$471, or \$523 million losses, respectively. Advertisers' harm is estimated even higher – 4.6%, 40.9%, and 45.5% of revenue losses under each policy.

Goldfarb and Tucker (2011b) analyze 3.3 million of survey responses and demonstrate that introduction of the European Union Privacy Directive, which limited the firms' ability to collect and use customers' data for targeting purposes, reduced the advertising effect on purchase intentions by 65%. In a field experiment conducted in the United States, Goldfarb and Tucker (2011a) show that in the states, where alcohol advertising is banned, survey respondents have 8% lower purchase intention for such beverages. The between-states difference drops to only 3% for the consumers exposed to online advertising, suggesting that substitutability of digital and traditional advertising may reduce the effectiveness of legal regulation of offline channels. Additionally, the larger detrimental effect of advertising regulations on the novel and low-awareness products provides evidence for the informative role of advertising.

Ohm (2013) points out that the firms may react on advertising bans by increasing the level of ad obtrusiveness to overcome the "harm" inflicted by the privacy regulations. He does not provide a formal economic model of the effect of advertising, but predicts a potential short-term decrease in advertisers' revenues and increase in the unemployment rate for the advertising agencies that fully rely on behavioral targeted advertising.

Thus, the empirical evidence on the effect of advertising restrictions is mixed: in support of the informative role of advertising, ban may result in higher prices, entry deterrence, and impeded information flow. However, policies that *restrict* advertising and online tracking, rather than ban the industry completely, may make both consumers and companies better off. Therefore, researchers and policy-makers should look for the more intricate tactics of advertising control. Next section summarizes some attempts to find an alternative solution for balancing buyers and sellers interests in the field of online advertising.

1.4.3 Alternative solutions

The concept of "intention economy" (Searls, 2013) is seeking to empower users' control over the access and use of their personal data. It argues that nowadays the companies are trying to react to the noisy signals about consumers' needs and preferences by sending them sometimes not accurately targeted or irrelevant offers, and sometimes even try to manipulate their behaviors and purchasing intentions (Calo, 2013). In response Searls (2013) suggests to invert the way the market is working now by giving the right to initiate the transaction back to consumers. He believes that the optimal equilibrium will be reached if the consumers will clearly state their needs on the marketplace, creating the competition among companies for the possibility to satisfy these needs. Uber and Airbnb are the popular examples of the first attempts to implement this idea.

Ohm (2013) sees a great potential in using less intrusive forms of targeted advertising, tailored to the context of the content, rather than to the users' online activities. He also predicts the rise of paid services, such as paywalls, in-app purchases, freemium business models, etc. Introducing payment for online services may reduce market inefficiencies and improve welfare by better matching the consumers' preferences and firms' offers through the price and reputation mechanisms (Strandburg, 2012). The back-of-the-envelope calculations in Budak et al. (2014) support the idea that a couple-of-dollar-fee for monthly subscription would cover the revenue loss generated by tracking prohibition. Some websites, for example wired.com and youtube.com, have already successfully adopted that strategy.

Strandburg (2012) strongly believes in legal reinforcement, development of technological solutions and privacy protective tools, business' self-commitment to treat users' data in ethical way, and wider adoption of such practices as privacy-by-design or Do Not Track (DNT) to be the important steps in the process of online advertising industry development.

Advertising industry itself tries to introduce and comply with some self-regulatory principles limiting tracking of the users FTC (2009). However, these programs are usually limited to affiliated organizations (such as DAA, AAAA, ANA, BBB, DMA, IAB) and require high awareness and proactive steps on the part of consumers. For example, opt-out cookies, which demand the manual updating and periodical renewal, can negatively affect user experience, and may be removed either by the third parties or, unintentionally, by the user himself (Mayer and Mitchell, 2012). Online behavioral advertising notices, such as AdChoice icon (Hastak and Culnan, 2010; Komanduri et al., 2011), and self-regulatory opt-out pages fail at conveying clear information about advertising practices (McDonald and Cranor, 2010) and suffer from usability problems (Leon et al., 2012). Moreover, Hernandez (2011) finds that only one out of ten examined ads contained the AdChoice icon. Thus, user choice mechanisms are shown to perform poorly and may undermine the faith in effectiveness of such methods and, therefore, discourage users from protective actions.

Users seek hopes in the deployment of ad-blockers. However, Madden (2015) reports that 54% of survey respondents think that it is difficult to find and deploy PETs, mostly due to lack of time and expertise, low motivation or disbelief that such tools are effective in preventing tracking. Apart from the usability problems (Leon et al., 2012), most of the current PETs fail to provide a fine-grained control based on contextual factors that affect privacy preferences (Melicher et al., 2015). Recently developed software, *e.g.*, Adnostic (Toubiana et al., 2010), Privad (Guha et al., 2009), RePriv (Fredrikson and Livshits, 2011), and CoP (Bilenko et al., 2011), limit the tracking of users' activities rather than just prevent exposure to targeted ads, destroying the root of privacy concerns instead of merely suppressing the visible symptoms. Nevertheless, the adoption of such sophisticated innovative tools requires changes in the advertising industry infrastructure that is currently poorly aligned with the ad-tech companies' interests.

Another trade-off between industry revenue and user benefits is to control the level of intrusiveness of online advertising and to allow only the least annoying ads to be displayed. For instance, Forbes[5] offers to its online readers "ad-light experience", but only for a limited time of 30 days. Upon expiration of the indicated time, it requires either to whitelist the website in order to enjoy its free content or to create an account providing personal details. Similarly, PageFair offers to publishers the services that show only not targeted "magazine-like" ads without animation. The more well-known Acceptable Ads program[6] launched by a popular ad-blocker, AdBlock Plus, calls advertisers, publishers, and ad networks to join them in manifesting recognition of not disrupting, annoying, or distorting the webpage content, but transparent and appropriate ads. However, Eyeo GmbH has been shown to accept payments from about 70 companies (including Google and Microsoft) in return for being whitelisted in the default configuration of the AdBlock Plus software (Marshall, 2015). This fact again impugns the effectiveness, transparency, and integrity of the self-regulatory approach.

Finally, Ohm (2013) calls for rising consumer awareness about data practices employed by companies, "encouraging social shaming", and triggering the active social movement against privacy-invasive practices, which unfortunately are becoming a social norm.

[5] http://www.forbes.com/
[6] https://acceptableads.com

1.5 Discussion and conclusion

In the recent years online advertising has become a rapidly growing and important market for global economy. Online marketing channels are believed to reduce the cost of advertising and to improve the seller-buyer matching due to a better understanding of consumers' preferences and personalized offers. Advertising industry emphasizes the positive influence of online advertising on marketing campaign effectiveness, business revenues, and even consumers' convenience. Nevertheless, the white papers may be apt to subjectivity. The customers-related consequences of online advertising do not gain enough attention in such discussions and sometimes are not even taken into consideration, while the fine-grained behavioral targeting comes with a cost for consumers: the vast amount of user data is collected over the Internet, triggering the rise of privacy concern. Moreover, low cost of digital advertising leads to excessive advertising intensity in the Internet and provokes reactance and nuisance among the users. As a result, many users are seeking protection by the privacy-enhancing tools. One of the most popular technological solutions is ad-blocking that filters advertising content on websites and in mobile applications.

The aim of this chapter was to summarize the evidence, both from industry report and, more importantly, from scientific sources, on the impact of online advertising on economy in general and on customers in particular, and to understand the role of privacy-enhancing technologies on consumers' welfare.

I started from the description of the state of the art in the fields of online advertising and ad-blocking technology and introduced the main terminology. In section 1.2 I summarized the theoretical findings and empirical evidence on the impact of advertising in traditional channels, such as print media, radio, and TV. I drew the particular attention to the models of targeted advertising in the traditional sense, *i.e.* tailoring ads to a general set of demographic and socio-economic characteristics of a particular audience. The conclusions of the scholars from various schools of advertising differ drastically and often oppositely directed. The advocates of informative role of advertising that see the main goal of ads in delivering the information about the brand, product, its price, and characteristics tend to derive positive effects of advertising on sales, competition, product quality, and consumer satisfaction. The supporters of persuasive view on advertising assume that advertising distorts the consumers' preferences and promote irrational brand loyalty. They are inclined to emphasize the entry-deterrence and adverse effects of ads on consumer surplus and prices. As explained by the both schools, the expansion of demand curve due to advertising may be related to different factors, such as change in product price; brand-, store-, or category-switching; redistribution; increased consumption; stockpiling; or use of savings. The predictions about consequences of the shift of demand depend on the assumptions of a particular model and on the view on advertising. The most popular effects of advertising on objective and perceived product quality and consumer satisfaction include repeat business, efficiency signaling, quality guarantee, and product matching. The conclusions of various groups of scholars are again controversial. The impact of targeting in advertising is typically viewed as positive if the practice does not preclude the exploitation of the consumers' reservation price for extraction of their surplus through price-discrimination, and quality deterioration. Moreover, the effect of personalized advertising on consumers' welfare positively depends on the accuracy of an employed targeting technique: the more relevant is the personalized offer, the more utility for a consumer has been generated due to targeting.

Although early theoretical models and empirical research studies did not take into account the peculiarities of online advertising, the distinction between roles of advertising holds for both online and offline advertising, and the general reasoning, patterns and most of the conclusions can be applied to the modern Internet advertising. First, the caution of all advertising school suggests to control advertising intensity, because excessive advertising volume blocks the generation of consumer surplus and social welfare growth, especially when the increase in advertising intensity is not accompanied by a decrease in product prices. The problem of excessive advertising volume is especially relevant for Internet channel, because programmatic ad buying, cloud storage and computing, RTB auction drastically decreased the cost and speed of advertising transactions. Web advertising did not substitute the traditional one, but augmented, while social media and proliferation of smartphones and mobile Internet have farther expanded the horizon of advertising space capacity, leading to virtually constant advertising overabundance. Such overabundance is one of the main barriers of social welfare in traditional models of advertising.

Second important aspect highlighted in the traditional marketing literature is related to targeting. It is true that modern technology permits the fine-grained personalization of advertising offers, increasing the relevance and timeliness of advertised products for the consumers. However, this targeting precision comes with a cost of extensive personal data collection, which in the models of traditional marketing channels used to be more limited. The tradeoff between personalization and privacy concerns is to be examined in the new models of online targeted advertising.

Third, the brand-, store-, and category-switching effects identified in traditional literature on sales promotion effects gains a larger scale in the electronic market. Aggregating websites (*e.g.*, Amazon, Trivago) have increased the substitutability of the products, and enhanced the comparison shopping. On the other hand, registration and creating profiles on the online vendors' websites generate users lock-in effects, impeding the customers switching. While traditional models predict redistribution of the resources and promotion of the competition rather than structural change in consumers' welfare, as a result of consumers switching behavior, the tradeoff between enhanced comparison shopping and strong lock-in and network effects is open to discussion in the modern research on Internet advertising.

Because the literature on traditional advertising gave many helpful insights about general impact of advertising on consumers' welfare, but did not answer to the novel questions specific for Internet advertising, in section 1.3 I moved the attention to the more recent literature on economics of advertising in digital media. As traditional advertising had a limited access to the user data, privacy implications of targeting in the early studies were often ignored. With the development of online tracking technologies, the amount of data collected from the users, often invisibly and without their awareness, has been grown exponentially, inevitably raising privacy concerns among the consumers. Therefore, excessive volumes and non-transparency conquered their places among the important factors negatively affecting the consumers' welfare through information and cognitive overloading, psychological reactance and discomfort, decreased productivity and accuracy of the decisions. While price discrimination has been already discussed in the early models of targeting in offline advertising, it gained even more attention in the theories about online targeted advertising as the ability, scale and precision of the reservation price extraction has been increased after the introduction of online behavior tracking technologies. Moreover, the dynamic nature of the Internet and search engine algorithms granted popularity to the price- and offer-steering practices manipulating the order of the shown products, for example, by demonstrating the most expensive products first to the customers that potentially have a higher reservation price. In line with the results of traditional advertising models online advertising models predict the positive effect of targeting on matching buyers and sellers, and reduction of the search and transportation costs, even though the latter aspect is becoming a less important factor in the e-commerce setting compared to the brick-and-mortar-store case. Omnipresent personalization of online information, from search results to ads, is shown to have a novel spillover of the reduction of consumers' exploration activities. With the support of empirical evidence from the literature I have shown that advertising message is required to overcome a number of obstacles, including, viewability issues, fraudulent clicks, ad-blockers, and mere users' attention limitations, in order to effectively reach a certain audience. Most of the times, the cost of failed impression rests on the shoulders of advertisers, publishers, and consumers, calling into question the claims of advertising industry about effectiveness of online advertising and behavioral targeting.

Moreover, the low transparency of tracking technologies and advertising accountability *per sé*, high concentration combined with the self-regulated management calls for action the antitrust authorities to investigate the market structure and underlay practices in greater detail. Currently one relies on the market forces to solve the conflict of stakeholders' interests, as most of the issues in online advertising are presently self-regulated by the industry. However, better understanding of the factors that can rock the boat of marketing campaigns' success may improve the predictability of advertising effectiveness and provide to policymakers the tools for regulation of the industry practices with a better protection of the customers' interests and market equilibrium.

Finally, as ad blocking may be considered a user-initiated advertising restriction practice, in section 1.4 I reviewed the theoretic and empirical literature on the effects of policies restricting advertising in order to derive the impact of privacy-enhancing technologies on consumers' and net welfare. The low cost of online advertising often pushes its overall volume beyond the socially optimal level, hurting both the businesses and their customers. At the same time the complete ban of advertising may lead to decrease in the quality of products, increase in prices, search and transportation costs, *etc.* Introduction of cap on the number of ad impressions per user or letting them to opt-out from receiving a certain type of advertising messages appear to be the better solutions for consumers' and net welfare. A better control of the advertising quality is required as well. Other alternative solutions for improvement of the market equilibrium include non-intrusive advertising requirements and their legal enforcement and intensity control, programs increasing consumer awareness and business transparency (*e.g.*, through consumer education and introduction of special informative icons and messages), and deployment of the new business models in which publishers' revenues do not heavily depend on advertising but rather on the monthly fees, additional paid services (*e.g.*, paywalls, freemium models, in-app purchases, *etc.*). However, a great attention is required to the potential side effect of introducing such payments as it may impede the access to information, especially for low-income and disadvantaged groups of people, complicating the existing inequality issue even further. Moreover, if the access to information from the independent and private media will be limited, it may increase the power of public information providers, hurting the competition and creating the favorable environment for politicization, information monopoly, opinion polarization, and governmental propaganda, especially in the countries under certain political regimes, with limited freedom of speech and loose monitoring and protection of the fundamental human rights.

Another group of scholars promote the development of intention economy, in which users prompt their purchasing intentions and companies compete for the right to satisfy the announced need. The success of the positive change in the established situation in the first place requires a shift in the social paradigm, which currently views the users as passive receivers of advertising content in bundle with the online services. Online users often find themselves helpless against the imposed conditions of using the Internet, with only few taking active steps towards protection of their rights, for example by using ad-blocking or anti-tracking tools. Enhanced awareness, and control are called to empower online users rights and privacy, to improve their experience and welfare, and eventually balance the interests of different stakeholders in order to achieve optimal general market equilibrium.

Chapter 2

Factors Influencing the Perceived Websites' Privacy Trustworthiness and Users' Purchase Intentions: Online Survey

2.1 Introduction

With development of World Wide Web and mobile technologies, electronic commerce has become a main driver of the digital economy. In 2016 e-commerce market achieved US$322,171 million revenue in the U.S. (Statista, 2016), accounting for 8.1% of total U.S. sales and 15.8% growth with respect to retail e-commerce sales a year ago (DeNale and Weidenhamer, 2016). In Europe, about 296 million online shoppers generated €455.3 billion e-commerce revenue in 2015, demonstrating a 13.3% increase with respect to the previous year (Willemsen and van Welie, 2016). However, the full potential of e-commerce has not been reached yet, as only about 43% of the European adult population shop online (Ecommerce News Europe, 2016). Therefore, investigation of the factors that may help e-commerce to reach its full potential is of high demand and relevance.

One of the main issues related to e-commerce is management of extensive flows of information, containing terabytes of personal data. Large amount of transactions and interactions between customers and companies now occur via online platforms and mobile devices. Together with benefits and reduced costs for market players, companies, and customers, it implies risks that range from nearly harmless to significantly pernicious, including tracking of online behavior and location, intrusive marketing, data breaches, *etc.*

Since online shopping precludes disclosure of personal information (*e.g.*, name and surname, credit card details, email and shipping address, *etc.*), it inevitably creates privacy concerns for some consumers, which, in turn, negatively affect their behavioral intentions (Dinev and Hart, 2006; Taylor et al., 2009). For instance, 61% of surveyed Internet users refused to buy online due to privacy concerns (Ryker et al., 2002) and 64% did so because they were not sure about how their personal information would be used (Culnan, 2001). As the result, inability to address privacy concerns induces customers to limit their activity in the Internet (Hoffman et al., 1999; Arnott et al., 2007; Doolin et al., 2007; Poon, 2007) and, in particular, inhibits online shopping acceptance (George, 2004) and leads to multi-million-dollar losses in online sales (Odom et al., 2002).

Many economic exchanges have experience- or even credence-quality nature, *i.e.* the quality and risks cannot be assessed before a transaction happens, and sometimes it cannot be estimated even after a transaction took place. Therefore, engagement in economic exchanges requires trust (Tullberg, 2008). According to social exchange theory, trust is one of the main business assets (Zucker, 1986; Luo, 2002). As e-commerce presumes virtual buyer-seller interactions rather than real, trust gains an even more crucial role in online shopping context than in brick-and-mortar stores. Therefore, trust becomes an important factor that drives online purchase intentions (Jarvenpaa et al., 1999; Grazioli and Jarvenpaa, 2000; Bélanger et al., 2002; Bhattacherjee, 2002; George, 2002; van der Heijden and Verhagen, 2002; Corritore et al., 2003; Gefen et al., 2003; van der Heijden et al., 2003; Pavlou and Gefen, 2004; Bart et al., 2005; Wu and Chang, 2005; Flavián and Guinalíu, 2006; Zhou et al., 2007; Kim et al., 2008a, 2012; Tariq and Eddaoudi, 2009; Chiu et al., 2010; Delafrooz et al., 2011; Islam et al., 2011; Al-Swidi et al., 2012; Ponte et al., 2015), and the lack of thereof prevents customers from completing e-commerce transactions (Wang et al., 1998; Furnell and Karweni, 1999; Hoffman et al., 1999; Gefen and Straub, 2000; Gefen, 2002; Grabosky, 2001; Grabner-Kraeuter, 2002; Lee and Turban, 2001; Pavlou, 2003; Kim et al., 2008a, 2011). For instance, NECTEC (2006) found that about 63% of online users prefer not to engage in online shopping due to lack of trust. Consumers are more likely to accept the perception of vulnerability when the website is trustworthy (Pavlou et al., 2006). Furthermore, the high level of trust propensity increases customers' satisfaction and positively influences repurchase intention (Chen et al., 2015) that may further improve online sales.

Therefore, privacy perceptions and trust are important factors influencing the success of business-to-customers e-commerce. A number of studies further demonstrated the negative correlation between privacy concerns and online trust in online shopping context (Cheung and Lee, 2000; Kim, 2001; Martin Jr et al., 2001; McKnight et al., 2000; Ngai and Wat, 2002; Malhotra et al., 2004; Eastlick et al., 2006; Van Dyke et al., 2007; Kim, 2008). For instance, consumers' privacy concerns were shown to decrease trust in vendor (Camp, 2002; Wu et al., 2012), while trust, in turn, reduces privacy concern (Milne and Boza, 1999; Taylor et al., 2009). Although Ponte et al. (2015) did not find the evidence of positive impact of perceived privacy on perceived trust in the presence of other, potentially stronger factors, the provision of privacy-friendly services may contribute to the construction of good reputation and help to gain trust that is proved to be one of the core elements mitigating concerns related to online shopping (*e.g.*, P&AB, 2005; Culnan, 2001).

Academic literature recognizes the presence of privacy concerns as one of the main inhibitors and trust as one of the main facilitators of online shopping acceptance. Because users often judge the trustworthiness of companies' websites based on the inspection of surface elements (Kim and Benbasat, 2003), it is important to understand what cues influence users' beliefs about credibility of these firms, and how these beliefs affect their willingness to buy from the vendors' websites. Therefore, present study aims at investigating the antecedents of consumers' perceptions of companies' trustworthiness with respect to privacy and the impact of these perceptions on subsequent purchase intention.

We present a model that maps the influence of various websites' attributes about companies' practices on the consumers' perceptions of companies' trustworthiness with respect to privacy, and their impact on purchase intentions. Using focus group we calibrate and then empirically test the model in an online survey with 117 adult participants. We found that privacy (including awareness, information collection and control practices), security, and reputation (including background and feedback) have strong effect on trust and willingness to buy, while website quality plays a marginal role. While generally trustworthiness perceptions and purchase intention are positively correlated, in some cases participants were likely to purchase from the websites that they judged as untrustworthy. We further discuss how behavioral biases, decision-making heuristics, and engagement in weighting risks and costs with expected benefitsmay explain the discrepancy between perceptions and behavioral intentions found in our study. Finally, we analyze and suggest what factors, particular websites' attributes, and individual characteristics have the strongest effect on hindering or advancing customers' trust and willingness to buy.

The paper is organized as follows: section 2.2 reviews related literature, presents a research model and related hypotheses; section 2.3 describes methodology; section 2.4 provides analysis of the results and testing of the hypotheses; and section 2.5 summarizes findings and concludes.

2.2 Previous studies and proposed research model

2.2.1 Definitions and concepts

Electronic commerce (hereinafter *e-commerce*) represents a system of "consumer-oriented storefronts, business-to-business applications as well as behind-the-scenes business functions like electronic payment systems and order management" (Conhaim, 1998; p. 13) and may take a form of business-to-consumer (B2C), business-to-business (B2B), and government-to-constituents (G2C). B2C e-commerce defines electronic business relationship between companies and individual consumers, B2B – between corporations, and G2C – between governments and different constituents (*e.g.*, firms, individuals, government agencies). In this study we focus on B2C e-commerce, defined as electronic business transactions conducted by a company electronically through its website directly to consumers.

Business models in electronic markets are broadly divided into 2 categories: e-marketplaces (or online exchange, brokerage) and e-tailers (or online retailers, merchants, e-shops) (Timmers, 1998; Applegate, 2001; Rappa, 2003; Hong, 2015). E-marketplace plays an intermediary role between buyers and sellers, matching them and providing web-based transaction services based on a brokerage fee (*e.g.*, NASDAQ, e-Bay, Amazon.com, Taobao, Kayak, *etc.*). E-marketplaces often aggregate the products from multiple sellers. E-tailer, on the other hand, is a storefront of independent merchant, usually an online version of traditional store (*e.g.*, Apple Store, Nike.com, *etc.*). In our study we will focus on e-tailers, to avoid the potential confounding between the trustworthiness perceptions toward a product manufacturer and a website selling it.

Trust is a multifaceted concept that includes interpersonal trust (in other individuals or groups of people), institutional trust (in institutions, such as government, university, financial market, healthcare, communication media, *etc.*), and organizational trust (in specific organizations and companies), and spans across a number of sectors, such as communication, politics, business, *etc.* While different types of trust are interrelated (*e.g.,* individual's organizational trust in a certain bank depends on one's institutional trust towards banking in general and interpersonal trust towards the staff and managers of this bank), the impact they have on decisions may differ. For example, interpersonal trust may be more subject to the influence of contextual cues (such as mimics, clothes, voice, mood), organizational and institutional trust is supposed to be more persistent and stable over time, and rely primarily on reputation and fundamental beliefs. For the purpose of this study we focus on organizational trust that occurs between customers and online merchants. Kim et al. (2008a) defines trust in an Internet vendor (including trust in the website itself, its brand, and a firm as a whole) as "a consumer's subjective belief that the selling party or entity will fulfill its transactional obligations as the consumer understands them" (p. 545) [1]. To control for the influence of interpersonal and institutional trust, we also collect information on general trust disposition, online shopping preferences, and the general attitude towards e-commerce. Most of the existing studies examined the impact of general organizational or institutional trust. As e-commerce raises high privacy concerns due to the extensive collection of personal information, which have a great impact on trust and purchasing behavior, we believe that a deeper exploration of the drivers and effects of domain-specific privacy-related trust on purchase intentions is worth studying. Therefore, present study

[1] See Czepiel (1990); Beatty et al. (1996); Jarvenpaa et al. (1998); Ratnasingham (1998); Hoffman et al. (1999); Brynjolfsson and Smith (2000); Gefen (2000, 2002); Urban et al. (2000); McKnight and Chervany (2001); Bhattacherjee (2002); McKnight et al. (2002); Ba et al. (2003); Corbitt et al. (2003); Gefen et al. (2003); Pavlou (2003) for alternative definitions of trust in e-commerce context.

focuses on a particular type of trust in an online vendor that occurs with respect to companies' privacy-related practices. We define *trust* with respect to information privacy in e-commerce context as a set of specific beliefs about another party not being engaged in opportunistic behavior such as selling, sharing, or other misusing of consumers' personal information. Such trust is expected to positively influence the individual's intention to conduct online transaction (Preibusch, 2013). Hence, *perception of trustworthiness* with respect to privacy, in our study, is a consumer's belief about characteristic of a company and its website that reports the level of online trust with regard to treatment of her personal data. Our definition of trustworthiness perception is close to the notion of privacy assurance in Lowry et al. (2012), based on the works of Kim and Benbasat (2003) and Rifon et al. (2005). They define privacy assurance as an "attitude that reflects how strongly a customer feels that their private information will be kept private by a website with which the customer is interacting" (Lowry et al., 2012, p. 756).

Some studies examined the positive relations between trust and willingness to provide personal information (*e.g.*, Hoffman et al., 1999; Cranor et al., 2000; Schoenbachler and Gordon, 2002; Bansal et al., 2015). Although personal information disclosure is usually a necessary step in online purchasing process (Ackerman et al., 1999) and may indirectly affect the likelihood of online transaction, in our study we focus directly on the willingness to make purchase as a measurement of behavioral intention. *Online purchase intention* is defined as a situation in which a consumer is willing and intends to make an online transaction (Pavlou, 2003). While actual purchasing decisions would be a more accurate measurement of consumer choices, the collection of such data is more problematic due to a larger cost of experiment, increased heterogeneity, and necessity of limiting the context to a certain product category and related price range, which would negatively affect the external validity and generalizability of the results. Although one may argue that willingness to buy a product does not always translate in the real purchase, the theory of reasoned action (Ajzen and Fishbein, 1980; Featherman and Pavlou, 2003) and theory of planned behavior (Ajzen, 1985, 1991) states that transaction intentions are positively correlated with actual transaction behavior. Therefore, we believe that purchase intention is an acceptable and reliable measurement of behavioral intent in our study.

2.2.2 Research model and related hypotheses

A number of models were developed in order to understand what influences users' online trust. For example, Cheskin and Archetype/Sapient (1999) report distinguishes six building blocks of trustworthiness: seals of approval, brand, navigation, fulfillment (including protection of personal information), presentation, and technology. Model in Corritore et al. (2003) consists of external and perceptual factors. External factors are related to trusters (consumers), object (website), and situation (level of risk and control). Perceptual factors include perception of credibility, ease of use, and risk. Bart et al. (2005) point out the heterogeneity across websites categories and consumers' characteristics and distinguish three main groups of antecedents of trust: consumer segment (demographics and personal characteristics), company's category, and website's characteristics.

Most of the trust models view trust as a general concept, while our study focuses on the trust particularly with respect to privacy. Liu et al. (2005) propose a privacy-trust-behavioral intention model that has the most relevant structure to the scope of our study. Empirical test of this model shows that privacy has a strong impact on users' trust in e-commerce, which in turn influences their behavioral intentions. Similarly, Chen and Barnes (2007) show that perceived usefulness, privacy, and security drive online initial trust, which then determines purchase intention. However, our model differs from the one in Liu et al. (2005) in several ways. First, we extend the number of privacy dimensions by including information collection, control, and awareness (Malhotra et al., 2004) instead of following the categorization of fair information practices (FTC et al., 2000). Second, we separate security and privacy features. Third, we include website quality and company's reputation that are shown to be the strong predictors of consumers' trust. Finally, we focus on willingness to make a purchase as behavioral intention measurement, because it has the most direct economic effect than websites visits, recommendations, or positive remarks about website.

Although we use our own model structure, we rely on the previous literature in choosing the factors for inclusion in the research model. Appendix A.1 presents the list of questionnaire items for our model. Factors influencing the perception of companies' trustworthiness regarding basic service provision (*e.g.*, shipment, ease of use, navigation, return policy, *etc.*) rather than information privacy were not taken into consideration in this study as they are beyond the scope of the research question.

While trying to estimate the trustworthiness of transactional partners, individuals rely on three main criteria: reputation, performance, and appearance. Reputation is viewed as retrospective of past behavior, performance – as overview of actual practices and present conduct, and appearance – as self-presentation (Sztompka, 1999). Following this taxonomy of trustworthiness assessment criteria, we include four dimensions of antecedents of trust in our model: *privacy* and *security* (performance criterion), *website quality and visual appearance* (appearance criterion), and *reputation* (reputation criterion). We will now discuss each of the dimensions in detail.

2.2.2.1 At construct level

Privacy Most of the trust models comprise privacy and security as the main cogwheels for online shopping acceptance (Keisidou et al., 2011), for establishing reliable long-term loyal relationship between companies and customers, and as antecedents of trust (Yousafzai et al., 2005; Kim et al., 2008a; Escobar-Rodríguez and Carvajal-Trujillo, 2014; Ponte et al., 2015).

Privacy assurances are shown to decrease privacy concerns, and increase trust (McKnight et al., 2002; Liu et al., 2004, 2005; Pan and Zinkhan, 2006; Lauer and Deng, 2007; Wu et al., 2012) and behavioral intentions (Wang et al., 2004; Meinert et al., 2006; Hui et al., 2007; Peterson et al., 2007; Tsai et al., 2011). However, some studies show insignificant (Wang et al., 2004; Metzger, 2006) and even negative (Arcand et al., 2007) effect of privacy policies on trust. Bansal et al. (2015) explain the contradictory nature of empirical evidence by the lack of attention to the level of privacy concerns as the factor mediating the effectiveness of the privacy assurance statements. Therefore, in our model we include the control variables that measure general level of privacy concerns.

Some factors included in our model are positive (*e.g.*, regarding transparency in providing information about privacy policies), while others are negative (*e.g.*, the prohibition to edit the list of permissions required during the installation of a mobile application) or even may have an unpredictably ambiguous effect on subjects' valuations (*e.g.*, when company asks a permission to use customer's current geographical location, on the one hand, it gives control over this piece of information to the user, but on the other hand, the intention to use geolocation may raise a privacy concern *per sé*). Therefore, we predict a significant influence of privacy-related practices on trustworthiness perceptions and purchase intention, but leave the sign of these relations open for exploration instead of imposing our personal opinion on that.

H1a: *Privacy-related practices have significant effect on trustworthiness perceptions.*

H1b: *Privacy-related practices have significant effect on purchase intentions.*

In categorization of privacy factors we follow the notion of Internet Users' Information Privacy Concerns (IUIPC) (Malhotra et al., 2004) by including *collection*, *control*, and *awareness* about privacy-related practices.

Collection considers the extent to which individual is concerned about the amount of personal data in possession of others relative to the perceived benefits and values. Collection is one of the main dimensions in the concern for information privacy (CFIP) scale (Smith et al., 1996) as well. Information collection category includes the aspects of business practices regarding the requirements and ways of the users' data collection, including deliberate information disclosure, take-it-or-leave-it offers, and implicit inferences about users' characteristics from observed behavior, *e.g.*, via tracking technologies such as cookies.

Control is related to the consumers' freedom of choice and ability to actively control (*e.g.*, approve, modify, opt-out, delete) their personal information (Caudill and Murphy, 2000). In the control dimension of our model we include the ability of users to grant permissions to the web services about access to the personal data, retention of the information, and freedom to choose a registration option.

Finally, *awareness* indicates passive control over personal information through being informed and understanding of the privacy-related organizational practices. It is related to transparency about collection, storage, use, and sharing of the information. Clear and credible privacy policies are shown to be helpful in building trustful relationships between online vendors and consumers (Schoenbachler and Gordon, 2002). FTC et al. (2000) recommendations about fair information practices suggest to use notices and appropriate disclosures about data procedural fairness in order to ensure consumers' awareness. Therefore, we include privacy policy statements and notice about use of cookies as factors designed to enhance user awareness.

Security Security issues have been found of a serious concern among online shoppers (Rao, 2002; Tsai and Yeh, 2010). Security perception indicates an extent of individual's beliefs that the website of online merchant is reliable against security threats (Meskaran et al., 2013). Security threats are "circumstances, conditions, or events with the potential to cause economic hardship to data or network resources in the form of destruction, disclosure, modification of data, denial of service, and/or fraud, waste, and abuse" (Kalakota and Whinston, 1996). A number of studies include security system assurances into antecedents of trust perceptions (Ambrose and Johnson, 1998; Kini and Choobineh, 1998; Teo and Liu, 2007; Ponte et al., 2015) and purchase intentions (Meskaran et al., 2013). Following the studies of Hawk (2004); Efendioglu et al. (2005); Meskaran et al. (2010, 2013), we also include a type of payment option as one of the antecedents of security perceptions.

H2a: *Security features have significant effect on trustworthiness perceptions.*

H2b: *Security features have significant effect on purchase intentions.*

Third-party assurance seals, which guarantee to the users that the visited website complies with the quality standards of particular operating practices and privacy policies, and ensure secure payment systems (Shapiro, 1987; McKnight et al., 2002; Kim et al., 2004) are strong predictors of security perceptions (Kimery and McCord, 2002; Furnell, 2004; Sharma and Yurcik, 2004; Jiang et al., 2008; Kim and Kim, 2011; Özpolat et al., 2013; Ponte et al., 2015) and credibility in relation to privacy (Xu et al., 2009; Lee and Cranage, 2011). While privacy seal is supposed to guarantee the website trustworthiness (Moores, 2005), a study of Edelman et al. (2006) shows that websites displaying TRUSTe certification are actually more likely to be engaged in privacy-invasive activities than uncertified websites. The evidence of the effect of third-party seals on trust is also contradictory (Özpolat et al., 2013): some empirical studies find a positive impact (Grazioli and Jarvenpaa, 2000; Miyazaki and Krishnamurthy, 2002; Rifon et al., 2005; Wakefield and Whitten, 2007; Yang et al., 2006; Hu et al., 2010), while others do not (Kovar et al., 2000; Bélanger et al., 2002; Mauldin and Arunachalam, 2002; Pennington et al., 2003; Bart et al., 2005; Hui et al., 2007; Kim et al., 2008a; Ray et al., 2011). Lowry et al. (2012) attribute such inconsistencies in empirical findings to a measurement error (indirect *versus* direct assessment of privacy assurance) and omitting of other important factors in the trust models. Supporting the finding in McKnight et al. (2002) they suggest website quality and brand image to have the strongest influence on privacy valuation. However, as Hoffman et al. (1999); Dayal et al. (2003), and Ovans (1999) argue, reputation and website quality features influence trust only after security concerns are addressed. We, therefore, test the relation between various factors in our model, and control for the familiarity with certifying agencies and for the understanding of the technical security features.

Some studies include security features in the notion of privacy (Liu et al., 2005), or even use privacy and security interchangeably (Ray et al., 2011). Others view the effects of privacy and security aspects separately (*e.g.*, Jarvenpaa et al., 1999; Bélanger et al., 2002; Casalo et al., 2007b; Tariq and Eddaoudi, 2009; Delafrooz et al., 2011). For instance, Bélanger et al. (2002) find that security features have greater effect than privacy statements, because security is a more concrete concept, which is easier for users to understand, than privacy. Similarly, empirical studies in Pavlou and Chellappa (2001) and Kim et al. (2008b) show a weaker effect of perceived privacy on trust compared to perceived security. Carlos Roca et al. (2009) argue that due to a better familiarity with security technologies, relative ease of recognition of its features (*e.g.*, certificates, encryption keys, password-composition requirements), and inclusion of some privacy guarantees in security assurance, perceived privacy has a smaller impact on trust for experienced users. Therefore, in our study we separate the impact of privacy from the impact of security features, and control for the technical and Internet experience of the participants.

Website quality and visual appearance Although privacy and security policies, statements, and seals are designed to directly influence privacy perceptions, they are shown to be more effective when combined with other, more peripheral, cues, such as brand image and website quality (McKnight et al., 2002; Lowry et al., 2012). Websites' design appeal is a course of attractiveness related to the visual presentation and structure of the website (Bansal et al., 2015) that signals website quality (Wells et al., 2011), expertise and professionalism, and develops trusting beliefs (Wakefield et al., 2004; Mayer et al., 2005; Dhamija et al., 2006). Fogg et al. (2001) consider aesthetics of the website as one of the important drivers of trust. Egger (2001) focuses on interface properties and design features, based on the assumption that consumers' trust in online business starts to form even before any online interaction has taken place. In his model of trust for e-commerce, pre-interactional filters that antecede interface properties are followed then by informational content. Moreover, trusting beliefs are positively correlated with the absence of errors on a website (Bart et al., 2005), accurate, current, and complete information (Kim et al., 2005), and correct spelling, grammar, and syntax (Koehn, 2003).

Another reason why visual cues are important antecedents of trustworthiness perceptions is explained by the signaling theory. Poor website quality or slow performance does not enforce users' beliefs that the company behind that website will do any better in privacy and security protection, or delivering services to customers (Bouch et al., 2000; Sillence et al., 2004; Bansal et al., 2015). Positive beliefs about firms' reliability, integrity, and professionalism are also related to the amount of time, effort, and money that company has invested in development and maintenance of the high-quality website, which is expected to proliferate and have an effect on other organizational practices including privacy and security related (Dawar and Parker, 1994; Duncan and Moriarty, 1998; Schlosser et al., 2006; Ray et al., 2011).

Hence, based on the findings in previous research, we include in our model the aesthetical quality factors, such as professionalism of the general visual appearance of the website and presence of the broken links and typographical errors on it. As users tend to believe that online advertising follow the norms of the websites containing this ad (Stewart, 2003), we include the presence of suspicious banner ads as one of the aspects influencing the assessment of website quality as well.

H3a: *Negative visual cues about websites quality negatively affect users' trustworthiness perceptions.*

H3b: *Negative visual cues about websites quality negatively affect users' purchase intentions.*

Firm's reputation Reputation (or store image), as a result of social evaluation and judgment, is a significant factor influencing the perception of website's trustworthiness (Smeltzer, 1997; Jarvenpaa et al., 1998, 1999; Grazioli and Jarvenpaa, 2000; Peszynski and Thanasankit, 2002; Yoon, 2002; Koufaris and Hampton-Sosa, 2004; Chen, 2006; Pavlou and Dimoka, 2006; Casalo et al., 2007a; Sillence et al., 2007; Song et al., 2007; Teo and Liu, 2007; Kim et al., 2008a; Meskaran et al., 2010) and purchase intentions (van der Heijden and Verhagen, 2002). Similarly to the visual appearance of the website, reputation of the company may serve as heuristic in signaling the reliability (Parasuraman et al., 1985; Dawar and Parker, 1994; Ganesan, 1994; Hosmer, 1995; Grazioli and Jarvenpaa, 2000; Gefen et al., 2003) and quality (Duncan and Moriarty, 1998) of the firm. Even though reputation is a primarily important antecedent of trust on the initial stages of the vendor-buyer interactions (Koehn, 2003), Ray et al. (2011) argue that it does not lose its role at the later stages of ongoing relationship due to the credence-quality nature of privacy, *i.e.* the level of privacy is difficult to assess even after the transaction has taken place, and therefore, users need to perpetually rely on a combination of sources to build and maintain trust throughout their relationship with a vendor.

H4a: *Good reputation positively affects users' trustworthiness perceptions.*

H4b: *Good reputation positively affects users' purchase intentions.*

In our study reputation is comprised of two main components: firm's *background*, and consumers' *feedback* about the company and its products.

Earp and Baumer (2003) report that consumers express higher willingness to disclose personally identifying and financial information to companies with well-known brand names. Brand image influences trust (Lowry et al., 2008). Familiarity in general has been shown as an important condition of trust in e-commerce (Luhmann, 1979; Bhattacherjee, 2002; Shim et al., 2004; Mollering, 2006). It reduces uncertainty (Gefen et al., 2003), concerns (Gulati, 1995), and increases perceived security control (Ray et al., 2011). Display of the information about company on the website, especially related to its offline presence (*e.g.*, physical address, contact details), reduces the uncertainty about otherwise "faceless" e-commerce (Fogg et al., 2001; Kim and Benbasat, 2003; Mayer et al., 2005; Kuan and Bock, 2007; Bansal et al., 2015). The impact of using photographs on the websites as a mean of creating the perception of social presence has no univocal empirical evidence. While some studies find a positive effect (Steinbrück et al., 2002), others show insignificant (Riegelsberger et al., 2003) or mixed results, and even consider photos as attempts to manipulate the consumers' online trust (Riegelsberger and Sasse, 2002). Therefore, *background* aspects in our study include well-known brand name, the number of years in business, and information about company's history, and names and photos of key people working there.

Jøsang et al. (2007) define reputation in e-commerce as a collective measure of trustworthiness based on referrals or ratings from members in a community. This definition is the closest to our notion of feedback. Customers' feedback (Resnick et al., 2000; Koehn, 2003; Walczuch and Lundgren, 2004; Lowry et al., 2010), third-party assessments (*e.g.*, rating services (Toms and Taves, 2004)) perceptions of social presence (Gefen and Straub, 2004; Hassanein and Head, 2004; Cyr et al., 2007; Hess et al., 2009), and, in particular, word-of-mouth within social network (Kuan and Bock, 2007) are shown to increase trust. Therefore, our *feedback* category includes customers' reviews, opinions in online social networks, and rating of the company in independent sources.

2.2.2.2 At item level

Selecting the items for survey we primarily focus on their relation to the main factors influencing consumers' attitudes that we will use later for the construction of indices. Analysis of the impact of these factors on trustworthiness perceptions and purchase intentions is the primary goal of this study. However, we are also interested in subtle differences between related aspects. For example, with respect to company's ranking we are interested whether there is a difference between online and offline sources of this ranking, or whether there is a difference between publishing customers' reviews on the company's own website or on the independent website, *etc.* Hence, we distinguish the following groups of related items: consumer feedback (FT/FP items 1, 2, and 5), ranking source (FT/FP 3 and 4), access conditions (LT/LP 4 and 5), source of information for recommendations (LT/LP 2 and 3), tracking (LT/LP 1 and 3), and app permissions (NT/NP 4 and 5). We will now discuss our predictions of the difference between the impact of the items within those groups.

Consumer feedback Online review credibility is positively related to the argument quality of reviews (Cheung et al., 2012). Unbiased pieces of information are more likely to be trusted (Sillence et al., 2004). Therefore, we predict that:

H5a: *Customers' feedback on independent websites has stronger impact on trustworthiness perceptions and purchase intentions than users' reviews on the company's own website.*

About 30% of favorable reviews are fraudulent (Liu, 2012) and authors of such manipulated opinions are often paid to promote companies and their products (Mayzlin, 2006; Hu et al., 2011b,a; Streitfeld, 2011; Kost, 2012; Tuttle, 2012). Consumers, aware of opinion fraud, may suspect overwhelmingly positive reviews to be fake. As consequence, a moderate amount of negative information in consumer review, as a proof of objectivity, increases its credibility (Crowley and Hoyer, 1994; Jensen et al., 2013). Such two-sidedness of exposure to both positive and negative aspects has been shown to have a bigger impact on belief change inducing fewer counterarguments and decreasing source derogation (Kamins and Assael, 1987; Kamins and Marks, 1988). However, in judgment and decision-making tasks individuals tend to rely more on negative information than on positive (Kanouse and Hanson Jr, 1987; Weinberger et al., 1981; Skowronski and Carlston, 1987; Herr et al., 1991; Feldman, 1966; Ahluwalia and Shiv, 1997). Metzger et al. (2010) find that users rely on negative reviews more heavily than on positive ones, possibly because negative information is perceived as more instructive and useful than positive information (Maheswaran and Meyers-Levy, 1990; Ahluwalia, 2000). Negative reviews have been to shown to have a greater impact on purchase intent as well (Weinburger and Dillon, 1980). Therefore, on the one hand, negative reviews may have a strong adverse effect on consumers trustworthiness perceptions and purchase intentions than positive ones, but on the other hand, presence of the solely positive feedback may appear suspicious to the customers, as some companies are known to pay for fraudulent favorable reviews. To test this idea, we propose the following hypothesis:

H5b: *Mixed (both positive and negative) customers' feedback has less impact on trustworthiness perceptions and purchase intentions than only positive users' reviews on the company's own website.*

Ranking source When source of information is perceived as more reliable and expert on a topic, consumers tend to associate a higher level of credibility to the message content from such a source (Giffin, 1967; Pornpitakpan, 2004; Ko et al., 2005). Improved ability of online media to aggregate information better enhances the determination of credibility than the traditional authorities (Flanagin and Metzger, 2008). The study of (Johnson and Kaye, 1998, 2000) and focus group results in Metzger et al. (2010) show that users perceive information found in online sources as more (or at least equally) credible than information in traditional sources. However, the "authority" heuristic (Hilligoss and Rieh, 2008; Sundar, 2008) suggests that users may perceive traditional sources of information as primary or official, and, therefore, develop a higher level of trust compared to the online ones. Traditional sources of information are believed to be unbiased and accurate (Mashek et al., 1997; Kiousis, 2001) due to established professional standards and social pressure (Finberg et al., 2002), while websites' content is not always subject to editorial review and factual verification (Flanagin and Metzger, 2000), even though Klein (2000) claims that the standards of accuracy are the same for both types of media. Moreover, social presence model (Short et al., 1976) claims that people tend to select the communication media with the highest level of social presence. Since social presence is positively correlated with trust (Gefen and Straub, 2004; Hassanein and Head, 2004; Cyr et al., 2007; Hess et al., 2009), while new (*i.e.* electronic) media is more suitable for the tasks requiring low social presence (Rice, 1993; Perse and Courtright, 1993), then, given the similar content in both sources, the offline source of information may gain a higher level of reliability and credibility than online one.

H5c: *Firm's high rating in the traditional media has a stronger positive effect on trustworthiness perceptions and purchase intentions than high rating in online sources.*

Access conditions As take-it-or-leave-it (TIOLI) offers do not allow consumers to access or use the services without personal information sharing, some users have to provide false personal information (Phelps et al., 2001) or abandon the website (EPIC, 2000). Hence, users are expected to dislike TIOLI offers more compared to the situations where they have more freedom in choosing the level of information disclosure.

H5d: *Users have higher perceptions of trustworthiness and purchase intentions towards websites that allow access to its content without personal information provision compared to the websites that do not grant such permission.*

Source of information for recommendations Privacy concerns include tracking through cookies and browser history (Wang et al., 1998). Perceived risk related to the online behavioral tracking may negatively affect the long-run relationships between online sellers and buyers (Jai et al., 2013), especially when consumers are uninformed about such practices (Nowak and Phelps, 1995; Lanier Jr and Saini, 2008; Turow et al., 2009). For instance, websites often track users for the sake of data collection and its use for remarketing and targeting purposes, *i.e.* delivering advertising related to the previous searches or other online activities. Aguirre et al. (2015) found that click-through-rates are lower when data for personalized online advertising was collected in a covert (*vs.* overt) manner. This effect may be related to the sense of vulnerability. Therefore, we expect users to generally dislike covert information collection practices over proactive information provision.

H5e: *Websites that explicitly ask to share information about tastes and preferences receive a higher score of trustworthiness perceptions and purchase intentions than those that implicitly collect such information using tracking technologies.*

Tracking The majority of users find targeted ads harmful, annoying, and "pushy", however, they are more comfortable with the first-party than third-party tracking, which is related to the higher degree of trust to the tracking party (Melicher et al., 2015).

H5f: *Third-party tracking has a more negative effect on trustworthiness perceptions and purchase intentions than first-party tracking.*

App permissions A finding about drop in click-through-rates after users have realized that information about them was collected without consent (Aguirre et al., 2015) provides evidence of the importance of both control over one's data and awareness about practices involving processing of personal information. Taylor et al. (2009) argue that the level of control over personal information does not have a significant effect on trust, but mediates the negative relationship between privacy concerns and behavioral intentions. To test this conclusion we add the following hypothesis:

H5g: *Trustworthiness perceptions about the web services that grant control over degree of personal information collection and willingness to purchase from them are higher than for the web services that do not provide such control.*

2.2.2.3 Covariates

Angst and Agarwal (2009) claim that more persuasive messages are required to affect the beliefs of highly concerned consumers. In accordance with Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1984; Sussman and Siegal, 2003), when assessing the trustworthiness, users, especially in their low-involvement and low-privacy concern state, tend to directly rely on the source credibility peripheral cues, such as reputation and visual design, instead of spending cognitive energy on effortful thinking (Taylor, 1981; Petty and Wegener, 1999; Bhattacherjee and Sanford, 2006; Wells et al., 2011; Bansal et al., 2015).

Although some studies show that disposition to trust plays an important role in assessment of credibility (Gefen, 2000; Kimery and McCord, 2002; Kim and Benbasat, 2003; Salam et al., 2005; Teo and Liu, 2007; Lowry et al., 2008), others do not find a significant support of such relation (Koufaris and Hampton-Sosa, 2004; Ponte et al., 2015). Lee and Turban (2001) demonstrate a mediating effect of propensity to trust on the impact of website attributes.

Internet experience is positively correlated with trust towards e-commerce (Corbitt et al., 2003). However, Aiken and Boush (2006) find an inverted U-shape relationship, where trust increases at the early stages of using web and then starts to decline because of rising privacy and security concerns.

Based on the suggestions of the previous literature, we collected via survey (appendix A.2) the information about participants' socio-demographic characteristics, such as gender (Q3), age (Q4), whether they live in urban area[2], source of income (Q10), monthly expenditures (Q11), technical[3] and Internet proficiency (Q13), online shopping preferences (Q17) and frequency[4], privacy attitudes (including general privacy concern (Q22), willingness to provide personally identifiable information to website (Q27), experience of privacy invasion (Q32), and Westin's index (Q33, see Westin (1968)), and trust disposition[5]. Additionally we include questions designed to elicit the understanding of Extended Validation certificate (coded as 1 if subject provided a right explanation of what does EV certificate mean in Q20, 0 otherwise) and cookies (coded as 1 if subject provided a right explanation of what does web cookie mean in Q21, 0 otherwise), and number of the third-party assurance authorities (*e.g.*, TRUSTe, VeriSign, *etc.*) with which subject is familiar (Q18). We also included the number of connections in the primarily used online social network (Q35) and whether subject uses real or pseudonymous name there (Q36). In contrast to the models that consider consumers' personal characteristics as one of the dimensions directly influencing trust (*e.g.*, Chen and Dhillon (2003); Gefen et al. (2003); Kim and Benbasat (2003); Bart et al. (2005); Ray et al. (2011)) we include them in the analysis as covariates.

2.2.2.4 The effects of cognitive heuristics and biases

The consumes' judgments regarding companies' trustworthiness may be affected by a number of cognitive heuristics and biases. Understanding of such phenomena may help to de-bias the decision-making process and improve the accuracy of judgments. Apart from the already mentioned theories (*e.g.*, ELM, social exchange and signaling theory, theory of reasoned action and planned behavior, *etc.*), the theory of bounded rationality (Simon, 1955) has a great potential in explaining the process that brings various factors into action to change the online

[2]"Urban" index was coded as 1 if subject lives in a city with >10,000 habitants (*i.e.* if answered 3, 4, or 5 in Q9), 0 otherwise.

[3]"Technical proficiency" index was coded as 1 if subject knows at least one programming language (Q12), 0 otherwise.

[4]The "frequency of online purchases" index is computed using a single-factor measurement model whereby answers to question Q16 are modeled as ordered logit (Cronbach's alpha = 0.8854).

[5]The "trust disposition" index is computed using a single-factor measurement model whereby answers to Q45-Q47 are modeled as ordered logit and answers to Q48-Q49 are modeled as logit (Cronbach's alpha = 0.7696).

trustworthiness perceptions. The notion of bounded rationality refers to the limitations imposed by the nature of human mind and exogenous conditions, and claims that individuals are constrained to make a decision using limited computational resources and time (Gigerenzer and Todd, 1999). This argument is further supported by *limited capacity model* (Lang, 2000) and *prominence-interpretation theory* of online credibility (Fogg, 2003) that argue that due to not infinite cognitive capacity individuals select only salient attributes for messages processing, which require an optimal level of cognitive effort to achieve a sufficiently efficient outcome (Pirolli, 2005). To reach that balance and make an adaptive choice people often employ cognitive heuristics (Hilligoss and Rieh, 2008; Sundar, 2008; Taraborelli, 2008; Metzger et al., 2010). Although such mental shortcuts and rules-of-thumb sometimes result in biased decisions (Tversky and Kahneman, 1975), more cognitively demanding information-processing strategies are shown to be equally (Gigerenzer and Todd, 1999; Gladwell, 2007) or even less effective in attempt to make a perfectly rational decision due their complexity.

The results of focus group in Metzger et al. (2010) identify four heuristics used by consumers in assessment of online credibility, which are relevant to our study: reputation (or authority), endorsement (conferred credibility), consistency, and expectancy violation. The *reputation heuristic* is based on the consumers' tendency to rely on familiar sources and alternatives rather than on unrecognized ones (Gigerenzer and Todd, 1999). People driven by that heuristic in our study may attribute a higher level of trustworthiness to a website that carries products with reputable names, or to a company that operates in business for many years and has a description of its history on the website. Alternatively, reputation heuristic may be a product of the *authority heuristic*, which suggests that degree of being an official authority or the information source is an important criterion of credibility assessment (Hilligoss and Rieh, 2008; Sundar, 2008). In our study the deployment of authority heuristic may be triggered by the presence of independent third-party seals, security features, such as icon of Extended Validation certificate compliance and trusted payment facilitators (*e.g.*, PayPal). Moreover, it may indirectly enhance the effect of the presence of key staff members' names and photos on the company's website, providing a proof of existence of real people behind the intangible web interface.

The *endorsement heuristic* (Hilligoss and Rieh, 2008), or *conferred credibility* (Flanagin and Metzger, 2008), is related to the confirmation bias and consensus (or "bandwagon" (Sundar, 2008)) heuristic (Chaiken, 1987), under which people perceive a source of information as trustworthy without scrutinizing the content if others already trust it. Projecting the observations in Metzger et al. (2010) on our study, we expect endorsement heuristic to have an impact on credibility perceptions through the reliance on consumers' feedback and reviews, online and offline ratings, and recommendations from friends in online social network. The impact of the latter factor is additionally supported by the *liking/agreement heuristic* (Chaiken, 1987) that suggests that individuals tend to believe that people they like possess the correct beliefs and to agree with their opinions.

The *consistency heuristic* predicts that information, which is similar across various sources, is supposed to be credible (Metzger et al., 2010). Our study does not presume cross-validation of information. However, in case it did, the consistency heuristic could increase the effectiveness of feedback if reviews on company's website and independent forums, or online and offline ratings coincided. This proposition can be addressed in the future research.

The first three heuristics are related to the notion of social proof (Cialdini, 1993), or social confirmation: if other users trust, use, and recommend some website, then one can also perceive it as trustworthy. However, such strategy is not perfect, as it may lead to misconception between credibility and popularity (Metzger et al., 2010), and in certain cases, to erroneous reliance on fraudulent information from manipulated opinions and fake reviews (Mayzlin, 2006; Hu et al., 2011a,b; Streitfeld, 2011; Kost, 2012; Tuttle, 2012).

Finally, the *expectancy violation heuristic* arises in the situations where websites' content does not conform to the users' expectations (Metzger et al., 2010) and as consequence of arousal, distraction, and increased attention to the violation (Burgoon et al., 2007) reduces the perceived trustworthiness of that website. In our study the effect of this heuristic may be illustrated by the situation in which website quality and design do not match the standards and norms (*e.g.*, presence orthographic and typographic errors, broken links, suspicious banners, *etc.*), or when website provides some unsolicited information or services not requested by the user (or what Sundar (2008) calls *intrusiveness heuristic*). It may take a form of company's products appearing on the unrelated websites, notifications about use of cookies, presence of the third-party websites' links, tracking, social network recommendations, remembering of the users' personal information, such as shipping address, credit card details, or login and password.

Figure 2.1graphically represents the proposed research model and related hypotheses. In our survey we asked people to consider each statement independently from other statements as if each item was describing a new company and to a full extent (*i.e.* nothing else beyond the information in a particular statement is known about each company). We did so to avoid the interaction effects and to elicit not the overall credibility perception towards a company and its website that possess a number of potentially contradictory characteristics but to assess a level of credibility attributed to each aspect separately. Therefore, although we grouped various aspects into distinct factors, these factors are not independent when considered together for an overall assessment of company's credibility or willingness to purchase from its website. For instance, we expect intercorrelation among privacy, security, and reputation, where fair practices regarding users' personal information contribute to the perception of how reputable the company is. At the same moment, reputable company is expected to aim at maintaining its reputation with respect to users' personal data as well, and therefore, to deploy high privacy and security standards. Similarly, a company with good reputation is expected to care about its image, and as website is a one of the channels for communication of brand image, such company is expected to exert efforts in creating a high quality website, while well designed website provides users with positive signals about reputation of the company as a whole. In contrast, website with poor quality raises doubts about professionalism of the people who built it, including their ability to ensure fair data collection and secure storage of this data, and therefore, creates concerns about privacy and security protection.

The discussion can be extended to the correlation between the effects of certain factors on trustworthiness perceptions and purchase intentions. Subconstructs may be correlated as well. For example, user may experience lower concern about data collection if he is aware about how this information will be processed and if he is given control over his information. The lack of or doubts about company's background may be mitigated by positive reviews from other customers, *etc.* Moreover, we expect positive correlation between trustworthiness perceptions and purchase intentions, so that users, who developed a perception of trust towards a company, will be more willing to purchase a product or service from its website.

H6: *Trustworthiness perceptions are positively correlated with purchase intentions.*

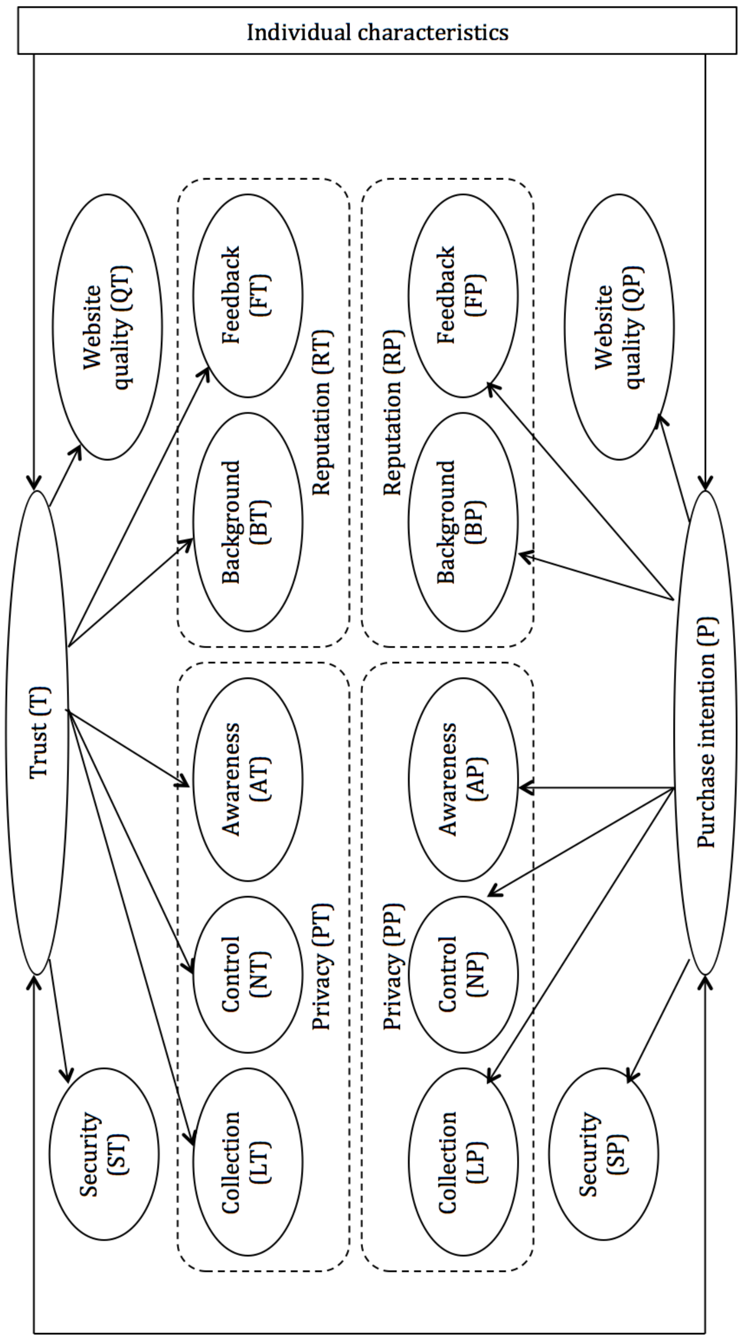
Thus, we aim to test the influence of four main factors (security, privacy, reputation, and website quality) on trustworthiness perceptions and on purchase intentions, and to compare the magnitude of impact of certain aspects in particular. We will then test intercorrelations among those factors, and the relation between trust and willingness to buy. Finally, we will run the robustness check with respect to individual characteristics.

2.3 Methodology

2.3.1 Data collection

Based on the related literature, we made a preliminary selection of the attributes and discussed them during two focus group sessions. The least prominent factors were sorted out. Then with 117 participants from the Mobile Territorial Lab (MTL) community we ran an online survey about trustworthiness perceptions and purchase intentions on the elaborated list of 32 statements about firms' characteristics and the aspects of their websites (hereinafter, *items*). The advantages of running the survey with MTL community members include low costs and wider demographic profile compared to a student pool usually used for academic research and criticized for being not representative of the general population. Each member of the MTL community (the total of 132 people) was contacted by the researcher and offered a chance to take part in the study. One hundred eighteen participants agreed to participate, and 117 eventually completed the online survey. Due to budgetary limits and because MTL community members already receive a monthly payment for participation in the subject pool for various studies, we offered a lottery-based compensation for participation in our survey as an incentive. Finally, we collected responses about demographics, prior Internet experience, online shopping acceptance, technological literacy,

Figure 2.1: Research model



privacy attitudes and concerns, and trust disposition through exit questionnaire (appendix A.2) and used them as control variables in statistical analysis.

2.3.1.1 Focus group

As a preparatory stage for the survey two focus group[6] sessions were conducted in December 2014 in the Cognitive and Experimental Economics Laboratory (CEEL), the University of Trento, Italy. During these roughly one-hour sessions the groups of six students (in the first session) and of seven students (in the second session) were asked in interactive setting about their perceptions, opinions, beliefs, attitudes, concerns, and habits towards e-commerce and online privacy. Participants were free to express their opinion and talk with other members. However, following the rules and principles of the focus group technique, a moderator (prof. Luigi Mittone) and assistant (Alisa Frik) administrated the discussion.

Participants expressed fairly high level of privacy concerns ("I'm not famous, but I'm concerned about my personal life and information"). Although one participant said: "Who cares about privacy nowadays!" others found the topic "relevant" and as "one of the most important", "fundamental", and "central arguments of the Internet use". In general, participants seemed to be quite pessimistic about the current state of privacy and called it "utopian" and "disappearing" concept.

As examples of privacy violations (personally experienced or known from other sources) participants mentioned hacking attacks on email services, iCloud, Playstation store, Twitter and Ebay platforms, PayPal and Yahoo password databases; Facebook behavioral targeted advertising and tracking of browser activity; consequences of losing mobile phone (access to personal files and accounts by unknown person, sending embarrassing messages and photos on behalf of the victim, *etc.*). As the reaction to instances of privacy violations online, the majority of participants described their discomfort, anger, irritation, fear, anxiety, and embarrassment, while the rest admitted their preparedness to such consequences ("I would not be surprised", "One should expect that") and perception of control over their data and ability to protect themselves from such violations ("It would be partially my fault, I should have protected my privacy").

As barriers of online shopping acceptance respondents indicated hazard of fraud, fishing, identity theft, data misuse, and general absence of trust. This observation proves the relevance of perceptions of trust to online shopping behaviors and necessity of examining the issue in detail.

After the discussion, several statements were added to the list, *e.g.*, about password creation requirements, friends' evaluation and opinion about the firm via a special widget incorporated into website's design as social network is gaining more weight in the seller-buyer communications. Some statements were corrected and clarified. For example, the statements about positive feedback

[6] Focus group is an exploratory technique widely used in market research, which collects through a moderated discussion the qualitative data from a small group of people on their opinions, beliefs, perceptions, and attitudes regarding a certain topic.

raised a discussion about their source and nature. Participants appeared skeptical about the fact that company has only positive feedback, suspecting it in falsification of reviews or deleting unpleasant ones. Thus, we included three different items to reflect the distinction: (1) about positive reviews on the company's own website, (2) about positive reviews on independent websites and forums, and (3) about the presence of both positive and negative reviews about the company on its website.

Based on the results of focus group the list of 32 statements about firms' attributes was developed. Qualitative results obtained in focus groups confirmed the relevance of the topic, while discrepancy among participants' opinions and attitudes proved the necessity of in-depth investigation of the issue.

2.3.1.2 Survey

As privacy attitudes are heterogeneous and context-dependent (Acquisti et al., 2016b), in this study we tried to focus on the more durable socially held judgments, and understand the "common knowledge" and type of cues that trigger the perception of trustworthiness rather than ask for personal opinions. Therefore, the survey was designed to capture perception about normatively appropriate privacy attitudes about the issue through incentivized elicitation method (Krupka and Weber, 2013). Participants were explicitly explained that the best strategy is to answer what they believe the majority of participants would choose rather than express a personal opinion about the argument. This method also permits to incentivize the choices and, therefore, elicit more accurate decisions.

Subjects were asked to read the list of statements (appendix A.1) about attributes of the firms and their websites (the order of items was randomized across participants). Firms were assumed to be retailers of homogeneous products and services hypothetically present on the online market. Each statement described the company completely, so that participants did not need to guess or imagine other characteristics beyond the provided description.

2.3.2 Measurements

After reading each statement, participants answered two questions on 12-point Likert scale. The response categories were assorted into 6 groups as it is shown in tab. 2.1.

After collection of the responses one statement and the related question were chosen at random. The score and category chosen by the majority of survey respondents were determined. Participants' who chose the "most popular" response for the picked item entered the raffle and 10 "winners" were chosen at random. They received a USB flash drive of 32 or 16 Gb (with a market price of 20 or 13 Euro, respectively) depending on whether they assigned an exact score or only a category as in the majority of respondents.

Statistical analysis of the result of the survey is presented in the next section.

Table 2.1: Survey questions

How trustworthy with respect to privacy the Web site of this company appears to the majority of other people, in your opinion?		How it is likely that other people will purchase products and services from the Web site of this company, in your opinion?	
Category	Score	Category	Score
Very untrustworthy	1-2	Very unlikely	1-2
Untrustworthy	3-4	Unlikely	3-4
Somewhat untrustworthy	5-6	Somewhat unlikely	5-6
Somewhat trustworthy	7-8	Somewhat likely	7-8
Trustworthy	9-10	Likely	9-10
Very trustworthy	11-12	Very likely	11-12

2.4 Results

We tested the research model using two-step structural equation modeling (SEM), where in the first stage we developed and evaluated the measurement model, and in the second stage we developed and evaluated the full structural model (Gerbing and Anderson, 1988). First, we ran SEM estimations on groups of items as endogenous observed variables and predicted the indices for sub-constructs as latent variables. Then we ran SEM estimations using predicted values of sub-constructs as endogenous observed variables, surveyed demographic characteristics and other covariates as exogenous observed variables, and predicted the indices for trust (T) and purchase intentions (P) as latent variables. Appendix A.5 summarizes the information about SEM path estimation. For the assessment of goodness of fit, we used absolute and incremental fit indices. Absolute fit indices include root mean squared error of approximation (RMSEA) and standardized root mean squared residual (SRMR), while incremental fit indices include comparative fit index (CFI) and Tucker-Lewis index (TLI). The conventionally acceptable values of RMSEA and SRMR should be ≤ 0.08, while the values of CFI and TLI are considered acceptable if ≥ 0.90 (Browne et al., 1993; Hu and Bentler, 1999; Hair et al., 2010). Tab. A.7 shows that the research model achieved the satisfactory level of goodness of fit.

Appendix A.3 summarizes the main statistics on measurements of trustworthiness perception and purchase intention by item. The highest evaluations of trustworthiness perception and purchase intention were assigned to the items ensuring privacy and security practices adoption, third-party certificates and high ratings in media, together with company's reputation, background, and variety of secure payment options. The lowest scores were assigned to the hypothetical websites that have low quality of content and design, are involved in the connections with third parties or actively try to encourage users to connect various accounts with the company's website, store users' personal details with or without consent, and offer recommendations based on the personal information about user.

Large standard deviation and variance may be related to the lack of participants' attention to the task, considerable diversity of opinions on the matters, or to the fact that the "collective perceptions" regarding web-based concepts are not mature enough yet due to fairly "young" and highly dynamic environment of the Internet, diversity in the level of technological literacy and intrinsic individual characteristics.

2.4.1 Reliability and validity

For the assessment of reliability we carried out confirmatory factor analysis with Varimax rotation. Using the Kaiser extraction criterion we retained only factors with eigenvalue > 1 for each construct. The resulting factor loadings were high (0.54-0.91); degree of uniqueness was within acceptable level of < 0.6 (0.18-0.6), for all items except LT1, QT1/QT3, QP1/QP3 (appendix A.4). Internal consistency of the resulting indices was good, Cronbach's $\alpha > 0.7$ (0.84-0.93), except for the website quality. Therefore, appendix A.4 demonstrates that the reliability of the measurement model is sufficient for all constructs and sub-constructs except website quality.

We tested two types of validity for the analysis of unidimensionality: convergent and discriminant validity. Convergent validity defines the extent to which each item converges to measures of other items that theoretically should be related. According to Hair et al. (2010) convergent validity exists if standardized factor loadings of each scale item is > 0.7, average variance extracted (AVE) is > 0.5, and composite reliability (CR) is > 0.7. Appendix A.5 shows that all constructs except QT satisfy these criteria demonstrating sufficient convergent validity.

Discriminant validity defines the extent to which an item diverges from other items that theoretically should not be related. The discriminant validity exists if AVE exceeds the shared variance measured as squared correlation for each pair of constructs and sub-constructs (Fornell and Larcker, 1981; Hair et al., 2006; Bove et al., 2009). Appendix A.5 shows that this criterion is not satisfied for all pairs of constructs and sub-constructs and that privacy, security, and reputation indices, including feedback and awareness, are often highly correlated. It suggests including the covariance between them in the path estimation model.

2.4.2 Relationship between trust and purchase intentions

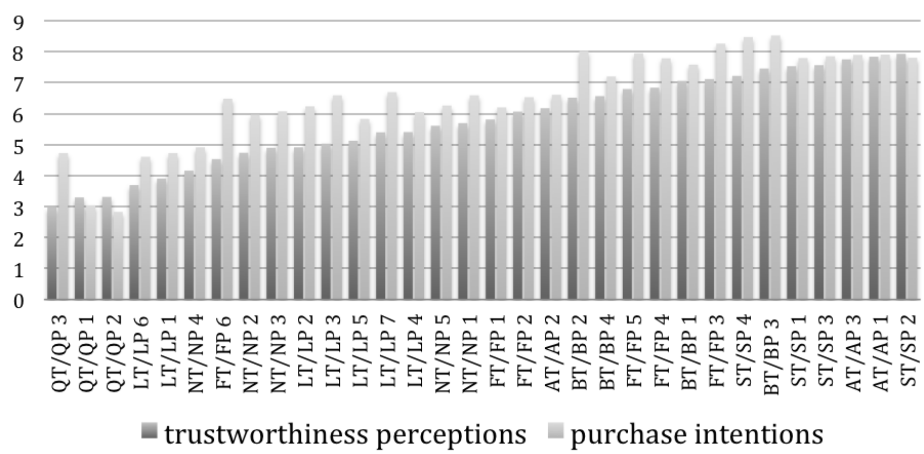
The results indicate significant positive relationship between trustworthiness perceptions and purchase intentions[7], at the aggregate level (*i.e.* between T and P) and at the sub-construct level (*i.e.* between ST and SP, QT and QP, *etc.*) as suggested by correlation and covariance coefficients (appendix A.6). This finding supports the hypothesis 6 about positive relationship between trustworthiness perceptions and purchase intentions.

[7] Pairwise correlation coefficients for each item are also positive and significant on 0.01 level and vary between 0.59 and 0.88 with average of 0.74.

Generally, positive correlation means that participants would be more likely to purchase from a trustworthy website and less likely to purchase from untrustworthy website. However there were some cases where valence of perception and behavioral intention were misaligned: participants rated some companies as untrustworthy with respect to personal information, but still were likely to purchase from them. Such misalignments of perceptions and behavioral intentions provide evidence for so-called "privacy paradox", *i.e.* the occasional inconsistency and disagreement between self-reported high level of privacy concerns and privacy-undermining behavior (Spiekermann et al., 2001; Berendt et al., 2005; Chellappa and Sin, 2005; Acquisti and Gross, 2006; Barnes, 2006; Norberg et al., 2007; Acquisti et al., 2016b).

Fig. 2.2 shows the distribution of ratings for trustworthiness perceptions and purchase intentions by item.

Figure 2.2: Mean values of the Likert scale scores of trustworthiness perceptions, and purchase intentions, by item



About 2.83% of the times participants reported negative intentions to buy from a website regardless of its positive value of trustworthiness. For example, privacy policy and password-composition requirements on the company's website (AT/AP items 1 and 3, and ST/SP 2) do not make participants necessarily more likely to purchase from the website even though it is perceived as trustworthy. This may be related to the fact that privacy is one of the factors influencing purchasing intention but not the most important driver of purchasing decision. In contrast, 14.3% of the times participants reported positive intentions to buy from the website to which they assigned a negative value of trustworthiness. This was particularly common for the BT/BP 3, LT/LP 2, 3, and 7, NT/NP 2 and 3, FT/FP 6, meaning that presence of the famous brands, widget from social network sites, possibility to access the website using social network account (so called "social login"), request of permission to access the geographical

location or of the information about tastes and preferences, inferring of such information using tracking technologies, and remembering the user's address for future deliveries have no or negative effect on perception of trustworthiness, however, it positively affects the purchase intention.

Most of the above-mentioned factors that trigger positive purchasing intention but negative trustworthiness perception offer privacy-invasive approaches to improve or speed up shopping experience. Thus, the misalignment observed in our survey may be related to the calculation of the credibility expectations that involves weighting of the expected costs and benefits implied by the decision to trust (Sztompka, 1999; Lane and Bachmann, 1998). Similar calculative approach was documented in privacy domain as "privacy calculus" (Laufer and Wolfe, 1977; Culnan and Armstrong, 1999; Dinev and Hart, 2006). However, people often fail to perform such calculation, for example due to *immediate gratification* (or *present*) *bias*, which refers to the individuals' preference for short-term returns (Anderson, 1971; O'Donoghue and Rabin, 2000), and *discounting* future costs and benefits (Laibson, 1994; O'Donoghue and Rabin, 2001; Jehiel and Lilico, 2010). In this perspective, website that offers the services that facilitate the online shopping process but are not privacy-friendly (*e.g.*, remembering of the personal details, recommendation systems based on behavior tracking) may generate a high willingness to buy even in the presence of low trustworthiness perception with respect to one's privacy, because the result of purchasing transaction occurs immediately, while outcome of the risks related to privacy untrustworthiness are uncertain in magnitude, value, probability, and time (John, 2016).

Consumers engage in e-commerce with a primary goal to purchase a product or service online, not to protect their personal information. Therefore, prominence-interpretation theory (Fogg, 2003) and low salience of the privacy-related factors with respect to shopping-related factors at the moment of purchasing decision process provide further explanation to the observed phenomenon. Moreover, in uncertain situations people tend to rely on contextual cues (Acquisti, 2004; John et al., 2011a). Websites are usually in control of such cues, as they make the decisions about website design, choice architecture, content, and structure of the information presented to the user. As websites' primary goals are related to business outcomes, they may firstly highlight shopping benefits, and draw less attention to (or even deliberately drive it away from) the potential privacy concerns and issues. In this case subjects are more likely to give a larger weight to the evidently and saliently presented benefits of a certain feature of online shopping experience rather than elaborate and assign the values to the potential risks that the decision may entail in privacy domain in the future.

Yet another explanation of why calculus may fail is related to the assumption of rational decision-making about trustor-trustee symmetry, while trust relationship between online vendors and consumers in reality is often asymmetric. Therefore, as predicted in Weber et al. (2004), with increase in dependency of trustors on trustees, the former (in our case consumer) decreases cognitive effort and information search required to assess credibility accurately, positively judges ambiguous information, and is inclined to engage in initial trust. In other words, as online e-commerce relationship often takes the form of take-it-or-leave-it offer, consumers have only limited decision options, while companies are in charge of creating and offering such options. For instance, a company can decide how much and what information to request from the user in exchange for providing the access to its mobile application. Even though the company asks the permission to access some personal information, the resulting outcome is conditioned on the user's consent. Therefore, if consumer does not allow the access to requested information, she does not have the access to a service the company provides. If the minority of the companies employed the invasive permission settings, users would have an opportunity to deny the access to their personal information and choose another company that provides similar services without requirement to reveal extensive amount of personal data. But proliferation and acceptance of invasive permission settings as a common business practice often leaves consumers without a choice (apart from saying "yes" or "no" to the use of a service) and, therefore, raises the user-website asymmetry in which users are more dependent on the conditions created by the websites than the latter are dependent on the consumers' choices. This situation makes users engage in initial trust if they want to use a certain service discounting some concerns that may accompany such a decision.

Moreover, combination of various factors is a tradeoff *per sé*. In our experiment we asked subjects to consider each factor independently, but real-life decisions are influenced by a simultaneous impact of a number of factors and their interaction effects. Consider for example, a website that requests some personal information in order to create an account and remembers a credit card number for future transactions but imposes strict password-composition requirements, ensures compliance with privacy regulations, and demonstrates security certificates. Request of personal information may create a privacy concern, but compliance with the privacy regulations and strict password-composition requirements mitigate them, by ensuring consumers that the information he provides will be treated fairly and securely. Similarly, remembering of the credit card details may be useful for faster future check-out process, but may raise a security concern. Presence of the security certificate mitigates such concern by ensuring consumer that the provided credit card details will be stored securely and protected from unauthorized access or use. Therefore, negative and positive aspects mitigate each other and the final decision and purchase verdict depend on the outcome of this interaction.

As a result of behavioral and cognitive biases discussed above consumers sometimes are willing to make a purchase from a website that is engaged in privacy invasive practices but facilitates or encourages purchasing process. This might explain why in certain situations, especially when the primary goal with which consumer enters the online space is purchase and not privacy protection, consumers make decisions not in favor of the latter. Thus, one should not rely on trust-related factors as the main predictors of sales, however, he should consider important mediating effect of trustworthiness perceptions on purchase intention. In the next section we will discuss what factors in particular are more or less influential for the consumers' choices.

2.4.3 Factors influencing trust and purchase intentions

2.4.3.1 At construct level

Standardized path coefficients (tab. A.6) suggest that all sub-constructs have significant effect on trustworthiness perceptions and purchase intentions on the 0.001 level, except for the quality of website. QT appears to have the smallest effect on trust, yet significant on 0.05 level. QP does not influence significantly purchase intentions. Therefore, our findings provide the support for H1, H2, and H4 for both trustworthiness perceptions and purchase intentions, and for H3 regarding the effect on trust.

As shown in appendix A.3, on average, websites' compliance with security regulations (ST and SP) results in the highest positive estimations otworthiness perceptions and purchase intentions, followed by awareness about employed privacy practices (AT and AP), company's background (BT and BP), and feedback (FT and FP). Poor website quality (QT and QP) leads to the lowest negative estimation of trustworthiness perceptions and purchase intentions, followed by the collection (LT and LP) and control (NT and NP) over personal information.

Therefore, companies with positive feedback and background appear to costumers as more trustworthy and elicit higher willingness to purchase from their websites. Moreover, ensuring consumers' awareness about security and privacy protection, by providing informational notices (*e.g.*, about use of cookies or practices related to collection, storage, sharing, and use of personal data), demonstrating the proof of compliance with privacy and security protection standards and regulations approved by independent authorities (such as Extended Validation certificates, privacy seals, *etc.*), enforcing password-composition requirements further improves users' trustworthiness perceptions and purchase intentions. At the same moment invasive practices of data collection and providing to users the limited control over this information (or poor communication of such control opportunities) lead to consumers' negative assessment of trustworthiness and subsequent purchase intentions. Although insufficient investment of time, money, and effort in the website design and low attention to the content quality do not have a significant direct impact on willingness to purchase, it may have an indirect effect through negatively influence trustworthiness perception, because of the correlation between trust and purchase intention demonstrated earlier.

In line with the low discriminant validity and high correlation indices, the covariance between some pairs of sub-constructs in our model is also significant (tab. A.8), for instance, between LT and BT, FT, NT; FT and NT; NP and FP, LP. This means that the company collecting users' personal information will be perceived as more trustworthy if it provides to the users control over the collected information, or has positive reputation, including positive background and feedback from other consumers. Similarly, practices involving collection of users' information (for example, for feeding the recommendation system, or for using the credit card details and shipping address for future orders and transactions) will increase purchase intentions more if it will be accompanied by the control over collected information. Such control may further enhance the positive effect of consumer feedback on trustworthiness perceptions and willingness to purchase.

Therefore, in order to build trust and increase consumers' purchase intentions companies should pay more attention to the way they present information about their reputation, including background, customer feedback and reviews, privacy- and security-related practices, and protection means. Moreover, they need to ensure a satisfactory level of the quality of this information, together with website content and visual appeal. Firms should grant users more control over their information, including traditional forms of consent or permission management, ability to modify/delete private data or deny the access to personal information, and also by providing a choice among alternative ways to access the website content (*i.e.* not only in in exchange for the personal information, but also on "freemium" or subscription basis for a small fee that allows avoiding private data collection, for example). We will now analyze in detail what practices tested in our survey are more effective in building trustful and effective buyer-seller relationships.

2.4.3.2 At item level

Consumer feedback Although one might find presence of solely positive feedback about the company on its website (FT/FP 5) subjective or suspect of fake reviews, on average, participants assigned a higher rating of trustworthiness and purchase intentions to such companies compared to the firms that have both positive and negative feedback (FT/FP 1 and 2)[8]. For the latter condition, having reviews on the company's own website (FT/FP 2) is not statistically different from such reviews on independent websites or forums (FT/FP 1) in terms of building trust and increasing purchase intentions[9]. Therefore, regardless of the fact that solely positive feedback is often fraudulent subjects tend to trust it more than a mixture of positive and negative reviews. Although it is easier for companies to manipulate reviews on their own websites than on the independent forums, subject do not seem to trust the latter ones more. Hence, our results support H5b but not H5a.

Ranking source The source of information about elevated position of the company matters for purchase intention, but not for trustworthiness perceptions[10]. Namely, high rating of the company in traditional media (FT/FP 3),

[8] Tests of the difference between (a) FT1 and FT5: t-test $Pr(|T| > |t|) = 0.00$; Wilcoxon rank-sum test: $Prob > |z| = 0.00$. Statistical power = 0.83; (b) FP1 and FP5: t-test: $Pr(|T| > |t|) = 0.00$; Wilcoxon rank-sum test: $Prob > |z| = 0.00$. Statistical power = 0.97; (c) FT2 and FT5: t-test: $Pr(|T| > |t|) = 0.00$; Wilcoxon rank-sum test: $Prob > |z| = 0.01$. Statistical power = 0.55; (d) FP2 and FP5: t-test: $Pr(|T| > |t|) = 0.0000$; Wilcoxon rank-sum test: $Prob > |z| = 0.00$. Statistical power = 0.96. N=117.

[9] Tests of the difference between (a) FT1 and FP2: t-test $Pr(|T| > |t|) = 0.15$; Wilcoxon rank-sum test: $Prob > |z| = 0.13$. Statistical power = 0.13; (b) FP1 and FP2: t-test: $Pr(|T| > |t|) = 0.10$; Wilcoxon rank-sum test: $Prob > |z| = 0.06$. Statistical power = 0.16. N=117.

[10] Tests of the difference between (a) FT3 and FT4: t-test $Pr(|T| > |t|) = 0.14$; Wilcoxon rank-sum test: $Prob > |z| = 0.18$. Statistical power = 0.12; (b) FP3 and FP4: t-test: $Pr(|T|$

such as TV and radio, results in a higher willingness to purchase from its website compared to the companies whose high ranking was acknowledged in online media sources (FT/FP 4). This finding suggests that respondents' willingness to purchase tend to rely on traditional media more than on online channels as the source of information about company's ratings and reputation. This may be because users are more experienced and familiar with traditional media, and feel more confident in relying on those sources. Moreover, the content published in traditional media is more likely to go through editorial review and approval (Johnson and Kaye, 2000). Hence, H5c is supported for purchase intentions but not for trustworthiness perceptions.

Access conditions The subtle difference between items LT/LP 4 and LT/LP 5 is that the latter describes a more strict access policy not allowing users to view the website's content without registration, while the former permits visualization of the content without sharing personal details and requests registration only when customers decide to place an order. However, average scores on both trustworthiness perceptions and purchase intentions for the websites with restricted access conditions did not significantly differ from the websites employing more privacy-friendly practices[11], providing no support for H5d. This finding may be related to the fact that restricted access condition is a common practice nowadays and thus does not raise strong concerns. Most online vendors require customers to create accounts on their websites. Such accounts not only help sellers to monitor customers' activity, but also allow consumers to keep track of their own transactions, save and compare products in the cart, save personal information (*e.g.*, credit card details and shipping address) for future transactions *etc.* Therefore, consumers may perceive benefits from registering on a certain website that in some cases outweigh corresponding privacy concerns.

Source of information for recommendations In contrast to our expectations that transparency regarding how the information about consumers' tastes and preferences is collected will be granted with a higher level of trustworthiness perception and willingness to buy, explicitly asking people about their preferences (item LT/LP 2), on average, did not result in different trustworthiness and purchase intentions scores than using of obscure tracking technologies to gather such information about users (item LT/LP 3)[12], providing no support for H5e. However, generally, the trustworthiness perceptions scores were negative for both items. Therefore, we can conclude that respondents equally dislike

$> |t|) = 0.03$; Wilcoxon rank-sum test: Prob $> |z| = 0.03$. Statistical power = 0.24. N=117.

[11] Tests of the difference between (a) LT4 and LT5: t-test $Pr(|T| > |t|) = 0.21$; Wilcoxon rank-sum test: Prob $> |z| = 0.25$. Statistical power = 0.12; (b) LP4 and LP5: t-test: $Pr(|T| > |t|) = 0.39$; Wilcoxon rank-sum test: Prob $> |z| = 0.14$. Statistical power = 0.09. N=117.

[12] Tests of the difference between (a) LT1 and LT3: t-test $Pr(|T| > |t|) = 0.00$; Wilcoxon rank-sum test: Prob $> |z| = 0.00$. Statistical power = 0.99; (b) LP1 and LP3: t-test: $Pr(|T| > |t|) = 0.00$; Wilcoxon rank-sum test: Prob $> |z| = 0.00$. Statistical power = 0.9995. N=117.

the collection of the information about their tastes and preferences, no matter implicitly or explicitly.

App permissions In support of H5g, providing an opportunity to edit at least partially the list of permissions before installation of the company's mobile application (NT/NP 5) significantly improves both the trustworthiness perception and purchase intention compared to the "take-it-or-leave-it" offer (NT/NP 4)[13]. Moreover, allowing users to modify app permissions is able to even alter the sign of purchase intentions, *i.e.* while respondents said to be unlikely to purchase from an app that inevitably accesses their personal data, providing a chance to edit the access permissions at least partially resulted in a positive willingness to make a purchase. Therefore, companies may benefit from enforcing privacy-friendly policies, not only on their websites but also in their mobile applications.

Besides the general effects of certain factors, such as reputation, security, privacy, and website design, we emphasize the importance of how these factors are then implemented. Appendix A.7 summarizes the results of hypotheses testing. Our results suggest companies to pay close attention to the way they design and implement their practices. For example, in order to build with customers the trustworthy relationships, which then positively affect purchase intentions, companies should try to avoid negative feedback, not through the review manipulation and fraud but through service improvement and consumers' needs satisfaction. Regarding the platforms, both independent forums and brand websites are effective in building trust. Firms should also enhance users' privacy and provide control over their personal information, for example through introduction of the privacy-friendly policies and editable lists of access permissions, and limiting collection of the users' personal data, either explicitly asking for it, or through opaque tracking technologies, such as cookies, algorithmic recommendation systems, *etc.* Although Internet media is gaining power, overtaking and sometimes even substituting offline channels in ability to build reputation and trust, companies should not forget to sustain and promote their image in traditional media, as it has a stronger influence on purchase intentions according to our results.

2.4.4 Robustness check

As a robustness check we controlled for the respondents' individual characteristics by introducing surveyed variables as observed exogenous covariates in the second stage of structural equation model estimation. In our model we assume that individual characteristics directly affect the latent variables that represent subjects' trustworthiness perceptions and purchase intentions.

The results show that females and older subjects tend to have a lower level of trustworthiness perceptions, while those who use real names rather than

[13] Tests of the difference between (a) NT4 and NT5: t-test $Pr(|T| > |t|) = 0.00$; Wilcoxon rank-sum test: Prob $> |z| = 0.00$. Statistical power = 0.99; (b) NP4 and NP5: t-test: $Pr(|T| > |t|) = 0.00$; Wilcoxon rank-sum test: Prob $> |z| = 0.00$. Statistical power = 0.96. N=117.

pseudonyms in Facebook are more disposed to trust. The latter observation suggests that the use of real identity in social networks may serve as a proxy for low privacy concern or high general trust disposition, which was found a significant predictor of trust in Gefen (2000); Kimery and McCord (2002); Kim and Benbasat (2003); Teo and Liu (2007). However, the number of connections (friends) in Facebook is negatively correlated with T and P. Although a big number of online social network connections could signal low privacy concern, it may actually decrease the level of users' trust as the audience to which one's personal information and activity is exposed gets larger.

Number of years that subject uses Internet is another factor that positively influences both trustworthiness perceptions and purchase intentions. This factor reflects elevated familiarity and experience with the Internet and is related to the enhanced adoption of e-commerce. Carlos Roca et al. (2009) argue that experienced Internet users may be more familiar with security technologies and therefore feel more comfortable about trusting the online shopping websites. Our result is in line with Corbitt et al. (2003) that found positive correlation between Internet experience and trust.

Subjects whose source of income is less independent and reliable (*i.e.* part-time job or spouse's support rather than full-time job) tend to have lower trustworthiness perceptions and, not surprisingly, lower purchasing intentions.

In contrast to our expectations, subjects' knowledge of programming languages as a proxy for technical skills, preference of online shopping *versus* offline, its frequency, and personal experience of privacy invasions did not have a significant effect on trust. Neither did the level of monthly expenditures, online shopping preferences and frequency has an impact on purchase intentions.

Direct measure of general privacy concern and Westin's privacy index both show that privacy-concerned subjects are less likely to trust the websites and buy from it. This finding further supports our claim about important relation between privacy, trust, and purchase intentions, suggesting companies to pay rigorous attention to customers concerns and ensure their personal information protection.

We observed that although almost half of the respondents recognized a symbol of websites' compliance with the Extended Validation certificate, only 72% of them understood correctly what this certificate means[14]. This misalignment may indicate potential misconceptions and misbeliefs about privacy and security signals. Qualitative analysis of the responses show that these misconceptions include the expectations that a website with a green padlock in the URL address bar will require registration for access or will constantly guard privacy of the users. Moreover, familiarity with privacy seal authorities, recognition of the Extended Validation certificate's green padlock and the actual understanding of its meaning did not significantly affect T and P. This findings are in line with previous research, which shows that although the website possessing independent certificates in reality are more likely to be untrustworthy than uncertified

[14]Note that participants had access to various sources of information during the survey and had opportunity to find and submit the correct explanation. Therefore, those shares of correct answers reflect the lower bound.

websites (Edelman et al., 2006), users tend to follow heuristics and shortcuts in relying on these assurances without verification of authenticity and not always understanding the meaning (Rifon et al., 2005; LaRose and Rifon, 2007), because according to signaling theory, in assessment of credence quality consumers may directly rely on cues (Zeithaml, 1988; Schlosser et al., 2006; Tang et al., 2008) even when they are not credible or interpretable (Duncan and Moriarty, 1998; Rao et al., 1999; Ray et al., 2011).

Similarly, 41% of the participants misunderstand the concept of web cookies. The respondents' explanations about meaning of this term range from "treats and sweets" to "informative windows", "users' feedback sent to the website to guarantee monitoring of the use", "files that permit a faster access to the Internet", and "some form of advertising". Some respondents called Web cookies "spies" and "garbage" that may be justified if considered metaphors. One of the respondents correctly drew the connection between cookies and subsequent receiving of targeted advertising, but erroneously concluded that one must enable cookies in order to avoid privacy invasion.

These findings suggest that the level of "privacy literacy" and awareness is still relatively low and requires consumer education. Misunderstanding may lead to the distortion of consumers' expectations and subsequent exploitation of such beliefs for fraudulent or malicious purposes. Therefore, these findings suggest further examination of the issue. Improvement of communication of privacy and security related information to the consumers is showed to be important not only for policy makers and privacy advocates but also beneficial for the business as enhanced trust contributes to increase in purchase intention.

2.4.5 Description of the subject pool

We distributed our survey to the Mobile Territorial Lab community members. This community has been created by Telecom Italia SKIL Lab and used as experimental environment for human-behavior analysis and interaction studies. The members of the community were selected and recruited among representative population of Italian mobile and Internet users. In contrast to most academic studies based on the students' responses we ran the survey with adults, representative of Italian Internet users population. Moreover, our sample is also representative of the European online shoppers population (Reinecke, 2015)[15]. Appendix A.2 summarizes the statistics about demographics and responses to the final questionnaire. 89% of the respondents are 35+ years old with 63% of the respondents being women, and the female respondents are on average younger than the male respondents[16]. 36% of respondents have only secondary education and 55% have bachelor or master degree, mostly in formal sciences, followed by social and humanity sciences. 77% of the subjects lived for the most

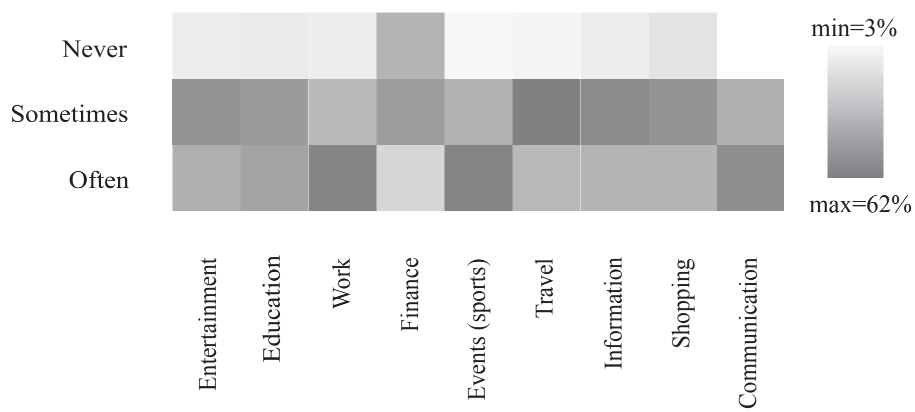
[15] 53-74% of 25-74 year-old EU-28 Internet users bought or ordered goods or services for private use over the Internet in 2014 (with negative relationship between age and percentage of online shoppers). 47% of those online shoppers have low education, 65% have medium education, and 78% have high education; 70% are employed.

[16] T-test: $p=.0338$ and Wilcoxon signed-rank test $p = 0.04$.

part of their lives in cities with 10,000+ inhabitants. 94% has full- or part-time jobs as the main source of income.

Nine respondents out of ten use Internet since more than 5 years, on average for about 19 hours a week. Fig. 2.3 summarizes frequency of use of the Internet for various purposes.

Figure 2.3: Heat map: distribution of the participants' responses about frequency of Internet use for various purposes



Eighty eight percent of respondents (which corresponds to 93% of males and 85% of females) use the Internet for online shopping (35% often and 53% sometimes), although slightly less than a half prefers to buy from a physical store rather than online. Most commonly respondents make online purchases for up to 500 Euro at least once a year (fig. 2.4).

Sixty three percent of the respondents do not know any programming language, while 18% know at least one and other 18% know 2-3 programming languages.

Seven out of ten respondents are familiar with at least one certificate authority or agency that focuses on ensuring compliance with the security and privacy regulations.

Generally, 44% of the subjects found it difficult to answer the survey. It may be related to the number of the items to be evaluated, each on two distinct constructs. Reducing the number of items and separating the tasks of evaluating trustworthiness perception and purchase intention in between-subject design could reduce the respondents' fatigue and improve the reliability of metrics.

Sixty-eight percent of the respondents are concerned about their online privacy; however, other 28% appeared to be rather indifferent, with remaining 4% being unconcerned. However, according to the Westin's Privacy Segmentation Index almost half of the respondents were classified as unconcerned, with

Figure 2.4: Heat map: proportions of the participants' responses about frequency of purchases from online vendors

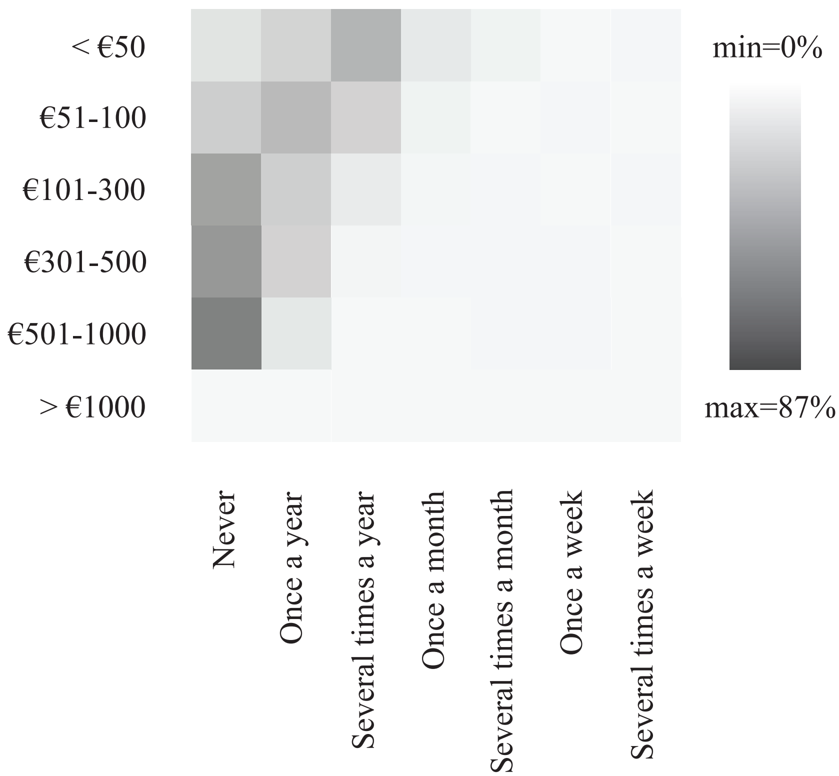
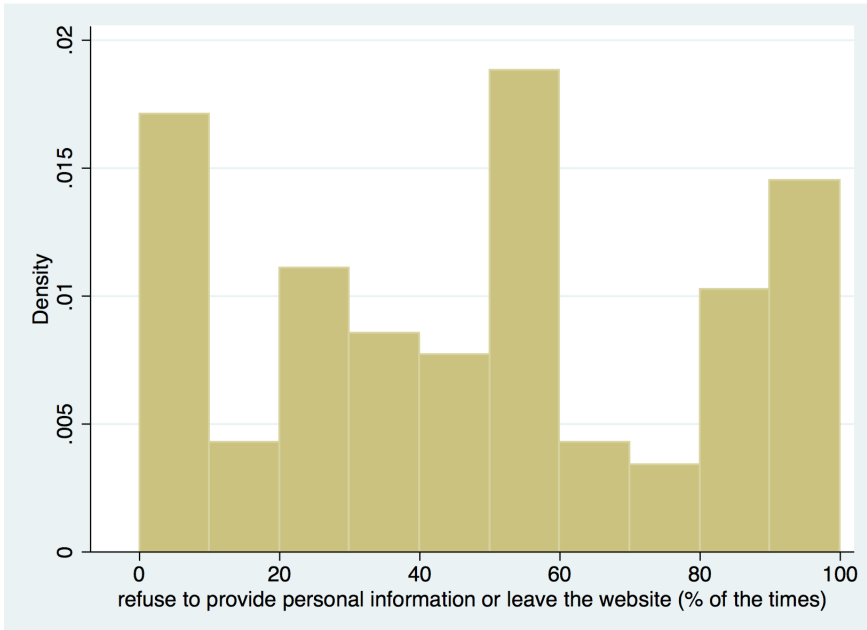


Figure 2.5: Distribution of the answers about % of the times participants refused to provide personal information or left the website



equal division of the rest between pragmatists and fundamentalists (27% each). Among various Internet issues the highest level of concern was assigned to the group related to privacy (62% are concerned about online activities being monitored and about personal information being stolen (77%) or misused (80%)), followed by concern about pornography being too accessible (76%), about receiving too many unsolicited email (56%). In response privacy concerns participants admitted to refuse or leave, on average, almost every second website requesting personal information (fig. 2.5). The alternative strategy of providing false information is less common and is used on average only in 10% of the times.

Underlining motives of refusal or providing falsified information can be combined into 3 main groups:

- privacy concerns: as an important reason for 93% of the respondents is the request of particularly sensitive information, lack of information about how personal data will be used (for 89%), the value of personal information exceeding the value that user would receive from the website (for 88%), and concerns about personal data being intercepted or stolen (for 82%);
- trustworthiness: bad reputation of the company (for 93%), lack of trust (for 91%) or familiarity (for 88%); and
- unsolicited correspondence: SMS (89%), email (79%), mail (75%).

Moreover, general preference to be anonymous was an important reason of refusal for 73% of the respondents, too much time required to fill out the forms (for 63%), and finally, lack of familiarity about how the technology works (for 54%).

A third of respondents personally experienced incidents of unauthorized use of their personal information by a company and almost a half (42%) - of privacy invasions.

Sixty seven percent of participants are not willing to provide personally identifiable and demographic information to websites while 19% feel indifferent about that. Almost two thirds would not provide it for the marketing purposes even in exchange for monetary incentives. Information about tastes and preferences are ready to share with websites a slight majority of the participants (38%), while 28% are indifferent about that. 69% would trade this information for marketing purposes if compensated. However, 80 to 90 percent of the respondents voluntarily revealed in the survey the names of their favorite books or films, sports and hobbies, even though it was irrelevant for the study information and questions were optional, i.e. could have been skipped without answer. It is possible that respondents draw a potential benefit of revealing preferences to the marketers that can target the relevant offers to them, while personally identifiable information seem to be less relevant for the marketing purposes and even raise a concern about price discrimination among savvy users.

A third of the respondents do not have a profile in social networks. Among those who have at least one account, Facebook is the most popular (37%), followed by Google + (12%), Twitter (6%), and Instagram (7%). A quarter of the respondents actively use 2 or more social networks. Since Facebook is the most popular social network among our respondents, we will further analyze this population: 56% of our Facebook users have no more than 100 connections on the website, and 15% have 100-200 or 300-500 connections. While 59% are convinced that their Facebook account is private and only friends can see it, this might be not entirely true, since some pieces of information, for example, name and profile picture are visible to the public. Taken into account that 94% of our respondents use real name, 69% use real photo and other 10% use their real photo with other people, the actual situation may not meet the users' expectations about their privacy on Facebook. Given that 32% never changed their settings while other 32% changed them only right after the registration, the situation seems even less optimistic from privacy prospective.

Finally, based on the "trust disposition" index, on average, our participants appear to be rather trustful than not trustful.

2.5 Conclusion

Based on previous research and the results of two focus group sessions we created a list of websites' attributes and tested their impact on users' purchase intentions and perceptions of trust with respect to privacy through a survey with 117 adult respondents.

First, we found that privacy, security, and reputation factors strongly affect trustworthiness perceptions and purchase intentions, while website quality plays a smaller role in building trust and has no effect on willingness to buy. On average, the websites with enhanced security, transparency regarding consumer privacy, and positive background and feedback deserved positive trustworthiness perceptions and purchase intentions scores, while practices related to personal information collection and control, and poor website quality raised concern regarding websites' trustworthiness and lowered the average willingness to buy from them. Intuitively, while privacy- and security-related aspects influence in the first place the perceptions of trustworthiness with respect to privacy, more shopping-relevant cues, such as selection of products with reputable names and payment options, are strong predictors of purchase intention. However, some factors, *e.g.*, firms' background and rating in media, are important mediators for both constructs. Although we asked participants to evaluate each item independently from other items, we eventually found positive correlation among some factors, which suggest the companies to design the multifaceted complex approach of trust relationships with customers.

Second, we found positive relation between trust and purchase intentions. It means that generally participants were more likely to purchase from a trustworthy website and less likely to purchase from untrustworthy website. This finding draws an attention of companies to the importance of building trustful and privacy-friendly relationships with their customers. However, in some cases participants that rated the companies as untrustworthy were still likely to purchase from their websites. This misalignment may be related to a tendency of expected benefits to outweigh the potential privacy costs resulting in willingness to make a purchase from a website that is engaged in privacy invasive practices. In other words, when a website offers a functionality that is expected to improve or facilitate online shopping process, but at the same time raises privacy concern, users' decision to trust and make a purchase from this website depends on whether benefits will eventually exceed costs, or *vice versa*. As individuals tend to discount future outcomes and to prefer short-term returns, immediate and evident benefits of improved shopping experience (which is also the main goal of engaging in e-commerce) may outweigh uncertain potential future privacy costs (which is a by-product of online interactions rather than a primary component). Moreover, privacy-related aspects may be presented on the website in a less salient way than shopping-related features, further enhancing underestimation of the weight of privacy components in the calculus of a final outcome of a decision. Finally, the asymmetric structure of the relationship between online seller and buyer put the latter in a position, which requires the latter to engage in initial trust accepting some risks in order to carry out a transaction. Such situations may force consumers to accept "take-it-or-leave-it" offer regardless concerns related to this decision.

Our findings suggest that leveraging the factors that positively influence trustworthiness perceptions may help companies to build trust that, in turn, affects consumers' purchase intention. First of all, companies should ensure security of their websites and, importantly, communicate the created level of security to the customers, for example, by introducing strong password-composition requirements and safe payment options, and demonstrating the compliance with security standards. Second of all, companies should pay great attention to the privacy-related issues, limit the collection of user data to the well-defined and user-friendly scope, be transparent about collection, storage, use, and sharing of this data, and give users control over their personal data. The forms of control should also evolve and improve over time together with the development of related technology and legislation. Companies should exert an effort in creating positive reputation, including presentation of the information about company's background, real people behind the website, allowing users to leave their feedback and respond to their concerns and questions. Firms, especially not well-known ones, should invest time, money and effort in creating a good-quality website which contains accurate and up-to-date information, as in situations of uncertainty visual appeal becomes an important peripheral cue and quality of the content signals the quality of the company itself.

Third, we found that participants trusted and wanted to purchase from the websites with solely positive feedback more than from the websites with mixed (both positive and negative) reviews, no matter whether it is published on the company's own website and on independent websites. Therefore, companies should pay attention to the customer negative feedback, try to solve the issues to achieve a higher level of consumer satisfaction and to publicly answer to the negative comments in order to maintain reputation. Respondents trusted online and offline source of companies' rankings in a similar way, however, the traditional sources appeared to have a greater impact on willingness to purchase. Therefore, companies should not forget to sustain their reputation in traditional media, even though the online sources of information are getting more and more popular nowadays. Our results suggest to limit or avoid tracking of customers' data, especially the third-party one, as users dislike it even more than first-party tracking. Moving away from "take-it-or-leave-it" offers and granting consumers with more control and choice is expected to benefit trust relationships and increase purchase intentions.

Finally, we found that people that use real name in Facebook rather than a pseudonym and are experienced in using the Internet, generally tend to trust the websites more, while females, older subjects, people with less independent source of income (*i.e.* without full-time job), higher levels of privacy concerns, and larger number of connections ("friends") in Facebook are less disposed to trust. Similarly, less independent source of income, privacy concerns, and number of Facebook connections negatively affect purchase intentions, while Internet experience has a positive effect. Therefore, in designing the trust-building strategies companies should be especially attentive to the above-mentioned target groups. Technical skills, the amount of monthly expenditures, frequency and preferences of online shopping, trust disposition, personal experience of privacy invasion, familiarity with privacy assurance agencies, Extended Validation icon, and understanding of the concepts of cookies and security certificates do not have significant effect on trust and willingness to purchase.

Moreover, we observed a relatively low level of "privacy literacy" among our respondents, as 30 to 40 percent of subjects have demonstrated the misunderstanding of the basic privacy and security concepts. Such misconceptions may distort users' expectations, lead to inefficient communications of the information, and cause economic or psychological harm. For example, the website that saliently present a notification about use of cookies may be perceived as less trustworthy than the one that hide it or collect information silently. Alternatively, users that think that cookies are essential for a faster access to the Internet, as one of our subjects pointed out, they may enable cookie storage without fully understanding the consequences it will have on their privacy. Improvement of communication of the privacy- and security-related information to the consumers is important not only for policy makers and privacy advocates but also beneficial for the business since the enhanced trust contributes to the increase in purchase intentions.

The present study has some limitations. First, it is based on the self-reported answers about hypothetical companies. Although it provides theoretical model and useful empirical insight about the factors influencing trustworthiness perceptions and purchase intentions, lab or field experiment with real e-commerce websites will further improve the external validity, accuracy of results, and allow testing interaction effect among various factors. Second, we used willingness to buy as a measurement of behavioral intentions, while future research may analyze the effect of proposed factors on real website visits, purchasing behavior, and repeated purchases.

Chapter 3

The Relation Between Privacy Protection and Risk Attitudes, with a New Experimental Method to Elicit the Implicit Monetary Value of Privacy

3.1 Introduction

The inspiration for this paper comes from our dissatisfaction with the currently established methods for assessing the value of privacy. The most popular methods include 1) experiments asking participants for their willingness to pay (WTP) to avoid getting private information revealed to others (alternatively, willingness to accept (WTA) payment to reveal their information), 2) surveys asking respondents for their feelings about a range of possible scenarios involving privacy, and for information about the way they handle various privacy concerns. While indeed suitable for a variety of applications, those methods suffer from two main weaknesses: 1) they are not incentivized (surveys) and 2) they do not correspond to the type of decisions that most people face when thinking about privacy (WTP and WTA experiments). Indeed, it rarely happens in real life to get offered payment for private information or to be asked to pay for information protection from a well identified, immediate and certain threat. Most of the time instead, people have to decide how much to invest to protect their information from a non-specific threat that may or may not be realized in the future and that has uncertain consequences. This means that actual privacy decisions are motivated by a mix of risk aversion and a desire to protect private information. We propose to disentangle those two aspects.

We make three main contributions in this paper:

1. We offer a new method to generate a privacy concern in the laboratory. We ask our subjects to fill a questionnaire about their opinions on a set of controversial, sensitive and socially relevant topics. This method overcomes the disadvantages of other methods used in privacy-related lab experiments, such as measuring and disclosing intelligence test scores, which create a dichotomous division between bad and good types and also suffer from an overconfidence bias. By covering multiple contexts, our questionnaire makes it very likely that at least one issue will be sensitive for an individual and, hence, induce a privacy concern for that individual. Our method does not require that individuals tell the truth about their own opinion. While eliciting information that is sensitive in the laboratory context, the personal information we obtained cannot be misused to damage the subjects materially, which helps to overcome legal constraints in the collection, storage, and use of personal information.

2. We test the analogy between standard financial risk attitudes and attitudes to privacy risk in a laboratory setting. We measure privacy attitudes in a context of risk by letting participants decide whether to take part in privacy lotteries, where the loss is a loss of privacy. Namely, we offer participants the option to play privacy lotteries that result in personal information disclosure with a certain probability. We compare decisions in such lotteries with decisions to incur risk in lotteries involving monetary outcomes. We find that attitudes to privacy risk correlate with attitudes to financial risk, as the best predictor for decisions in privacy lotteries is attitude to financial risk. We test this result for robustness by introducing the risk of a privacy shock in one treatment – there might be personal information disclosure regardless of the individual's effort to protect it. This does not alter choices in privacy lotteries. We also test this result for an order effect, and find that subjects lose interest in protecting their privacy if preferences in privacy lotteries are elicited after the monetary ones.

3. Based on those findings, we offer a novel methodology of implicit elicitation of equivalent monetary values for one's personal information by comparing choices in monetary and in privacy lotteries. Our two-step indirect elicitation method allows us to obtain implicit monetary values for privacy, corrected for risk preferences in so far as those influence the decision to incur privacy risk. Our method can be applied for any type of private information; it is not limited to the particular type of personal information about opinion on sensitive social topics that we used in our experiment. Indeed, the loss of privacy can be in the financial domain, about health, about one's social network, etc.... Moreover, this method is not limited to the exposure of subjects to a risk of personal information

> revelation but may be applied to a range of other risks, such as unauthorized sharing with third parties, use of contact details for unsolicited marketing purposes, exposure to fraudulent activity, *etc.* We argue that our method is more suitable than direct and explicit valuation methods for the purpose of accurately evaluating and comparing the perceived disutility of privacy risk in various domains, especially when direct elicitation is not feasible or may undermine the validity of the study.

The paper is organized as follows: section 3.2 reviews related literature and presents our hypotheses; section 3.3 describes the experimental design and methodology; section 3.4 provides an analysis of the data and tests of the hypotheses; section 3.5 provides a discussion and robustness check of our results; section 3.7 describes our method of estimation of monetary value for privacy; and section 3.8 summarizes our findings and concludes.

3.2 Related work and hypotheses

With the more widespread use of the Internet for a wider range of daily activities, the interest in privacy issues has spread beyond a personal concern, raising a debate about privacy issues from economic, legislative, technological and policy perspectives.

The empirical validation of privacy models, and further elaboration of policies and solutions in terms of regulation, protection, exchange and use of personal information raise a serious measurement challenge: what value does personal information have, to whom, and under what conditions? Two main approaches that researchers took to investigate these issues are surveys and experiments.

A Jupiter Research survey (Leathern, 2002) reported that 36% of US respondents would allow tracking of their Internet activities for a US$5 discounts. A similar fraction of European respondents agreed to trade their e-mail addresses for money or a chance to win a prize (Symantec, 2015). However, another survey found that 91% of Americans disagree with the statement that "If companies give me a discount, it is a fair exchange for them to collect information about me without my knowing" (Turow et al., 2015, p. 3). Although numerous surveys report high privacy concerns in the general population of both the U.S. and Europe (see Turow et al., 2015; Madden and Rainie, 2015; Eurobarometer, 2015), the hypothetical questions in surveys and the complexity of privacy attitudes make it difficult for the researchers to quantify the preferences of participants and predict their behavior. Acquisti et al. (2016a) remark that stated preferences usually differ from observed behavior and suggest that privacy attitudes are idiosyncratic, subjective, context-dependent, and dynamic, *i.e.* change over time (see also John et al., 2011b).

In order to address issues in quantifying privacy preferences and to estimate the value people assign to their personal information, researchers have turned to experimental and empirical methods. A field experiment of Beresford et al. (2012) elicited an average willingness to accept 1 Euro in discounts in order to provide date of birth and monthly income to an online DVD store. Gideon et al. (2006); Tsai et al. (2011); Egelman et al. (2013) demonstrated that some customers were willing to pay a premium to purchase from privacy protective websites, while Hann et al. (2007) found that "among U.S. subjects, protection against errors, improper access, and secondary use of personal information is worth between US$30.49 and US$44.62" (p. 29). Anecdotal evidence in Grossklags and Acquisti (2007) suggests that people accept even small rewards of 25 cents to sell their personal information, but are not ready to spend the same amount for its protection. Huberman et al. (2005), using experimental auctions, found a correlation between trait's desirability and bid for protection from revelation of information about this trait. For instance, they showed that young people were more likely to reveal their age than the older population (on average, for US$3.62 and US$18.05, respectively). Similarly, the higher is the perceived discrepancy between one's own and the average weight of other subjects, the lower is the willingness to reveal the information about one's weight. Benndorf et al. (2014) elicit a willingness to sell contact details for 15 Euro and Facebook data for 19 Euro in their incentivized experiment using a DBM mechanism. 10 to 20% of their participants did not want to sell personal information for any price. As one can see even from the limited sample of findings presented above, privacy preferences differ dramatically across individuals and studies.

All those studies ask people directly for their willingness to sell or protect information. However, Wilson and Brekke (1994) claim that explicit measurements may limit the motivation, opportunity, and ability of people to retrieve, translate and report mental contents. Sometimes such contents are even not accessible to introspection. Moreover, subjects are more inclined towards extreme values in explicit measures than in implicit measures (Schwarz, 1999). In contrast, implicit measures provide an assessment of mental content without intentional deliberate processing and awareness about the relation between derived response and mental content (Nosek and Greenwald, 2009), and therefore, avoid limitations typical for self-reported estimations (Nosek et al., 2011). Empirical studies showed that neither of the measuring techniques is "truer" than another (Banaji et al., 2004), and that both explicit and implicit measures may have a stronger or weaker predictive power in various domains (Nosek et al., 2011). Therefore, in our study we develop a new, implicit measurements of personal information (dis)utility but we also elicit the same measurements as previous studies for comparison (*e.g.,* Westin's Privacy Index, WTA/WTP, general privacy concern). We do not claim to find an absolute value for privacy, but offer a novel experimental approach of eliciting behavior in an incentive compatible way that can be applied in various domains for a better understanding of individuals' preferences.

To the best of our knowledge, our experiment is the first attempt to test the relation between risk and privacy attitudes in a laboratory setting. Dinev and Hart (2006) found that privacy risks and concerns are closely and positively related. Our first hypothesis is that decisions to protect personal information will be correlated with attitude to risk; participants who are risk-averse in monetary lotteries will also be risk-averse in privacy lotteries.

H1: *The willingness to protect personal information from the risk of revelation will increase with aversion to the risk of a monetary loss.*

We will test this hypothesis by checking if there is a correlation between the willingness to protect personal information elicited in privacy lotteries and the risk tolerance level elicited in monetary lotteries. We will test this result for robustness by running a treatment with an unavoidable risk of privacy shock – under the assumption that losing control on the decision to take a privacy risk changes attitudes to that risk. We will also check if the order of elicitation (first monetary risk then privacy risk *vs.* vice versa) primes our subject to think of privacy like a monetary good.

Our second hypothesis is that direct valuation methods and privacy attitudes elicited in surveys will correlate with the willingness to incur a privacy risk.

H2: *The willingness to protect personal information from the risk of revelation will increase with WTA/WTP for privacy protection and will correlate with survey measures of privacy attitudes.*

If the above hypotheses are verified, then we will feel justified in deriving an implicit monetary value of privacy by comparing decisions in monetary and privacy lotteries. We will compare this indirect elicited implicit value of privacy, as derived from decisions in our experiment, with directly elicited explicit values of privacy.

3.3 Experimental design

Subjects were asked to make a sequence of binary choices between safe and risky options. Subjects faced two types of lotteries: *monetary* lotteries that imply changes in monetary outcome; and *privacy* lotteries that imply the disclosure of personal information.

3.3.1 Personal information

In order to create privacy concern, we combine different sources of data (that we will collectively refer to as *personal information)*: *standard* personal information and personal information that was elicited in the lab. Our standard privacy items were the name and surname of participants. Those remained unknown to others unless the outcome of the experiment was such that the subject had to reveal them at the very end of the experiment. We also took photos of each subject upon arrival in the laboratory. Combined together, those pieces of data can be classified as personally identifiable information according to McCallister (2010). Moreover, from full name and photo one could potentially infer additional information, *e.g.,* gender, age, ethnicity, and sometimes even religious views and health issues (for example, myopia due to the use of eyeglasses).

Our source of private information consisted of answers to a questionnaire (appendix B.1), with 14 questions about opinion on potentially sensitive or socially relevant topics, such as abortion, illegal immigration, and appropriate methods of birth contraception. This questionnaire was filled in before subjects received instructions about the experiment (appendix B.3). This personal information was then put under the risk of disclosure in the laboratory experiment.

Multiple mechanisms were design to create and enhance privacy concern in the laboratory setting. There is no right or wrong answer in such a survey, and opinions create a "personal image", potentially exposing differences in opinion among the subjects.[1] The psychological literature states that the fear of being isolated from other people imposes a psychological cost on subjects expressing unpopular opinion (see Noelle-Neumann, 1974; Kim, 1999; Clemente and Roulet, 2015).[2] Behaviors and opinions that deviate from group's norms and expectations are also more likely to be ridiculed or even punished by the group (Griskevicius et al., 2006; Janes and Olson, 2000; Kruglanski and Webster, 1991). Our experimental design did not preclude creation of the group identity, which would be undesirable in our study, because high level of familiarity among participants makes it easier for the subjects to predict group's norm and respond accordingly, while uncertainty about the consequences of personal information revelation strengthen privacy concerns and psychological discomfort related to expressing an opinion. Nevertheless, majoritarian opinion may represent the "norm" in our context. If the information was to be revealed to others, responses to the preliminary questionnaire appeared not in a general summary, but in a comparative form, confronting the answers of the individual with the share of people with contradictory opinion. Such presentation allowed to compare the subjects' responses with the prevailing view, which can be considered a norm, locally emerged in a group of subjects participating in a certain experimental session. Our design also aimed at avoiding the truth-telling issue. There was no way to escape the possibility that one's expressed opinion will conflict with the opinion of a portion of other participants, and this did not depend on whether one's expressed opinion corresponds to one's truthfully held opinion. Moreover, since questionnaire questions were presented in the form of multiple choice options rather than open questions, participants did not have opportunity to explain or defend their positions.[3] The potential fear of being "misunderstood" is expected to further enhance the discomfort with regard to information disclosure and privacy concern. Therefore, no matter whether the subject answered truthfully or not, the risk of public revelation of the opinions together with name, surname and photo, the uncertainty of consequences, the

[1] Even if a participant did not report a truthful answer, he sent a signal about his type that would contradict the position of people from an opposite group. Intra-class correlation coefficient among answers on preliminary questionnaire equal to 0.56, proving that we managed to achieve this goal with a good level of nonconformity among participants, in the sense that a large proportion of subjects expressed opinions that differed from others. See shares of answers to the preliminary questionnaire, mean and standard deviation in appendix B.1.

[2] Nonetheless, nonconformity could appear advantageous in certain circumstances, *e.g.,* if subjects attempt to emphasize their uniqueness or individuality (see Argyle, 1957; Hollander, 1958; Maslach et al., 1985; Snyder and Fromkin, 2012, *etc.*).

[3] Indeed, during the experiment several participants raised the question about such a possibility and expressed concern about absence of such.

fear of public "shame" in case of deviation from an established local group norm, is expected to cause privacy concerns.

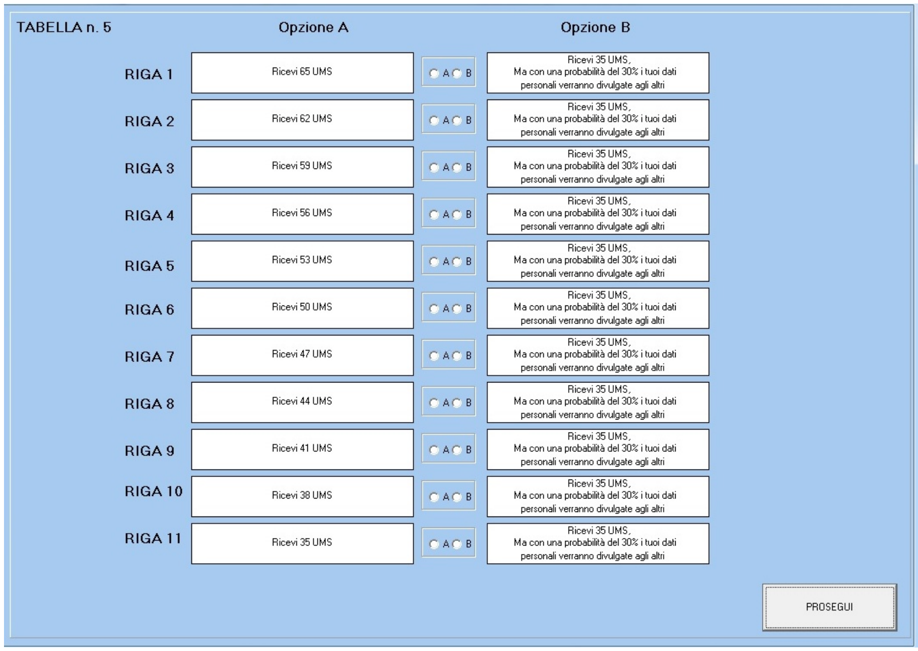
There are a few other experimental studies that *synthetically* produce personal information for the purpose of investigating privacy attitudes. Rivenbark (2012) used a public good game to endogenously generate valuable private information for further elicitation of values and beliefs. Grossklags and Acquisti (2007) used quiz performance to estimate willingness to sell or protect personal information. Feri et al. (2016) created sensitive information via a logic test score connected to the real name of the participant. The personal information we elicit in the lab is less artificial and more broadly relevant than the synthetic information generated in those experiments. Our method overcomes the disadvantages of using intelligence test scores, which create a dichotomous division between bad and good types and are affected by an overconfidence bias (Griffin and Varey, 1996; Wallsten, 1996), whereby people have a tendency to believe that they belong to a group with a test score above median. Moreover, our questionnaire covers multiple contexts, thus increasing the probability of capturing an issue that is sensitive for an individual and, hence, of inducing a privacy concern without falling into issues with truth-telling. While eliciting information that is sensitive in the laboratory context, the personal information we obtained cannot be misused to damage the subjects materially, which helps overcome legal constraints in the collection, storage, and use of personal information.

3.3.2 Elicitation method

We elicited risk attitude by asking subjects to make choices between gambles in a variation of multiple price list (MPL) designs that are commonly used in experimental economics. MPLs are easy to understand for participants and are incentive compatible (Miller et al., 1969; Holt and Laury, 2002; Harrison and Rutström, 2008; Andersen et al., 2006). Subjects were offered 8 lists, each requiring 11 decisions between two options: safe options and risky lotteries (fig. 3.1). Subjects were asked to indicate the option they preferred to play for every row. The order of MPL menus within each task was randomized across participants.

The option A offered a safe payoff x, while option B offered an outcome y, which was decreased by c with probability $1 - p$ in monetary tasks. In privacy tasks, outcome y came with a probability $1 - p$ of having to disclose private information. We varied option B across tables, while safe payoffs x in option A was lowered from the top row to the bottom row. According to Maier and Rüger (2010), keeping the probabilities fixed and varying only the outcomes helps to avoid the issue of probability weighting, assumed in standard parametric prospect theory (Tversky and Kahneman, 1992). Moreover, comparison of numeric outcomes is easier for participants than comparison of event probability. We set $p = 70\%$ (so the probability of a loss of money or of privacy disclosure equals 30%) because while 50/50 chance is more neutral and rather suitable for monetary lotteries, a 50% probability of personal information disclosure is

Figure 3.1: Screenshot of one of the MPL menus in the privacy task



too high with respect to what may be consistent with real world probabilities of privacy breaches. However, setting p higher would lead us into a domain of probabilities that are difficult for subjects to grasp intuitively.

Monetary lotteries In the monetary task we presented to subjects menus of choices between safe payoffs x and lottery L, while varying payoff y and the loss c. c was either a loss of 10 ECU, 30 ECU, or 50 ECU ($c = 10$, 30 or 50), or a gain of 30 ECU ($c = -30$). Payoffs x varied from slightly above y to slightly above $y - c$ if c was a loss, and from $y - c$ to y if c was a gain. Appendix B.5.1 shows MPL menus as they were presented to the subjects. We varied losses and gains to be able to condition our measure of risk aversion for a subject to the level of loss he is facing. This is because we do not know in advance what value a subject attaches to privacy, and we therefore need to consider risk aversion for a range of possible values.

Privacy lotteries In the privacy task, we showed to the subjects the same menus of choices as in monetary lotteries, except that we replaced monetary loss c with an obligation to reveal private information. That is, in the risky options, subjects got y ECU, but with probability $1 - p$ their personal information was disclosed to other participants in the lab. Values of x, y, and p were the same as in monetary task (see the corresponding MPL menus in appendix B.5.2).

The proposed risk elicitation technique is not limited to the type of data used in our experiment and can be easily adapted and applied to other kinds of personal information. For example, privacy lotteries could also imply revelation of financial and health information or of information from social network accounts. Our method allows the measurement of the (dis)utility of privacy risk in various domains.

3.3.3 Treatments

We designed two conditions to check robustness to an order effect: in the first, the privacy lotteries appeared prior to the monetary lotteries; in the second, the monetary lotteries appeared before the privacy lotteries. We also ran two treatments to test the effect of control deprivation: in the *basic* treatment the outcome of the experiment depends solely on the choice of the participants, providing them with full control over their personal information; in the *shock* treatment participants faced a risk of privacy shock, *i.e.* probability of revelation of their personal information independently from the choices in the experiment. We discuss those treatments in section 3.6.

We thus have a 2×2 treatment design (basic *vs.* shock, and privacy first *vs.* monetary first). Subjects were assigned to each of the four groups at random. Treatments were implemented as between-subject, so that each participant faced either a situation where the risk of privacy shock was present or absent and either the monetary or the privacy task appeared first. Within-subject analysis allows comparison between the choices of every participant across the two tasks (monetary and privacy lotteries).

3.3.4 Procedure

The experiment was conducted in the Cognitive and Experimental Economics Laboratory between May, 4^{th} and June, 8^{th} 2015. A total of 148 subjects were recruited for 8 experimental sessions, in groups of 15-21 participants per one-hour session, among undergraduate students at the University of Trento, Italy. Appendix B.8 summarizes the demographic characteristics[4]. On average subjects obtained 8.83 Euro per person, including a 3.00 Euro participation fee.

When invited to participate, our subjects were not told that the scope of the study was related to privacy. However, they were given an opportunity to decline participation in the experiment after reading instructions for the experiment and the questions of our preliminary opinion questionnaire. The payment of show-up fee was guaranteed independently on that decision. Thus, we controlled for self-selection related to reluctance to respond to the questionnaire or jeopardize privacy. All invited subjects decided to go through with the experiment.

To improve the clarity of decision consequences, we employed the prior incentive system (PRINCE) (Johnson et al., 2015a). Instead of picking one of the decisions for payment only at the end of the experiment, we distributed closed

[4]The demographic characteristics were similar across all sessions.

envelopes with a description of the real choice situation that will determining an individual's payoff *before* the experiment started.[5] This system makes it more obvious to the participants that any situation might be relevant for them, and which decision is relevant depends on the chance that has already realized at the moment they picked an envelope. Therefore, it was more obvious to participants that they have to consider each decision they make as potentially payoff-relevant. Johnson et al. (2015a) claims that PRINCE system improves understanding that the payoff-relevant decision is chosen at random, and gives better reassurance that this is true randomization, *i.e.* that the experimenter is not deceitful. This also makes isolation of each decision "maximally salient" (p. 3) and makes the issue of hedging across decisions (Holt, 1986) less important.

We introduced the risk of privacy shock in the shock treatment by adding 24 envelopes that determined the payoff independently from the choices made in the experiment. Thus, with 21% probability subject would pick up an envelope, which implies sure payoff of 35, 55, 65 or 75 ECU and revelation of personal information, no matter which choice they had made in the tables.[6]

After subjects picked at random an envelope, they entered the laboratory and took their randomly assigned seat. After completion of the preliminary questionnaire subjects read the instructions for the first part of the experiment. Once all participants answered correctly to the control questions (appendix B.4) they proceeded to the first task of the experiment. After participants finished the first task, they read instructions for the second part of the experiment. Upon completion of the second task participants answered a final questionnaire (appendix B.2) about the experiment, basic demographic information, attitudes towards privacy, WTA and WTP for personal information, risk, self-disclosure, fairness, and trust.

At the end of each session subjects came one-by-one to the experimenter's table and opened their envelopes. The situations described in the envelope were implemented. In the situations, where personal information had to be disclosed to other participants, the subjects stood in front of the audience in the lab, experimenter verified his name and surname from the ID card and announced it aloud. Other participants saw on the screen the personal photo and the answers that subject gave in the preliminary questionnaire. To emphasize the inequality aspect mentioned in section 3.3.1, we presented the summary of the answers to the preliminary questionnaire in a form of comparison with the fraction of participants who answered in a different way, *e.g.,* "John Smith agrees that it is morally justified to abort after discovering serious disability in the fetus, while 93% of other participants does not agree".

We now proceed to the description and analysis of the experimental results.

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[5] Decision-makers find it easier to condition on the events determined in the past rather than in the future (see Keren, 1991; Shafir and Tversky, 1992; Cubitt et al., 1998; Hey and Lee, 2005; Bardsley, 2010).

[6] Note, that our design avoids an issue of compound lottery. Since subject picks an envelope at random before the experiment, the presence of privacy shock is determined by the state of the nature. Thus, the only risky decision a subject is free to make is to choose option B in MPL menus instead of safe option A.

Table 3.1: Interval estimation of *ror* across MPL tables.

MPL table	Range of safe outcomes (in ECU)	Lottery option	Elicitation interval for *ror*
1	46 - 56	Get 55, but Pr=.3 to lose 10	$-7\% < ror < 13\%$
2	38 - 68	Get 65, but Pr=.3 to lose 30	$-18\% < ror < 47\%$
3	30 - 80	Get 75, but Pr=.3 to lose 50	$-25\% < ror < 100\%$
4	35 - 65	Get 30, but Pr=.3 to gain 30	$-32\% < ror < 26\%$

3.4 Results

In total our data set is made out 88 binary choices made by 148 individuals. In 95.86% of cases participants switched from the safe to the risky option in a MPL table only once.[7] They thus demonstrated monotonic preferences across lotteries.

3.4.1 Risk preferences

For our measurements of risk attitude, we calculate the ***r**ate **o**f **r**eturn* ("*ror*") required by each subject to take the lottery. A subject who is indifferent between safe payoff x and monetary lottery $L = (y, 1-p; y-c, p)$ requires a rate of return of:

$$ror = \frac{y \cdot p + (y - c) \cdot (1 - p) - x}{x} \tag{3.1}$$

Expressed another way, $x \cdot (1 + ror) = y \cdot p + (y - c) \cdot (1 - p)$.

We use the midpoint of the interval in which a subject switches between the safe and the risky option as our measurement of x, the certainty equivalent of L. Adopting the idea that back-and-forth switching behavior could be the result of indifference (see Andersen et al., 2006; Harrison et al., 2012; Charness et al., 2013), we use the mean value between the lower bound of the first switch and the upper bound of the last switch in MPL table as our estimate of x in cases where subjects switched more than once.

Tab. 3.1 shows that with our choice of monetary lotteries, we are able to obtain an estimate of the risk premium even for very high or low values of *ror*. If a subject never switched in a table then we consider the level of *ror* to be unobserved for that subject in that table. If a subject never chose to play a lottery in any table for any value of the safe alternative then we consider this subject to be infinitely risk-averse. If a subject always chose the lottery rather than any safe option then we consider this subject to be infinitely risk-loving.

We compute $\overline{ror}$, the average *ror* by individual. On average, the level of $\overline{ror}$ was 11%. We find that 127 subjects (86% of the total) were risk averse ($\overline{ror} > 1\%$), 16 subjects (11% of the total) were risk seeking ($\overline{ror} < -1\%$), and

[7] This is consistent with proportions of 93.4-94.5% observed by Holt and Laury (2002).

5 subjects (3% of the total) were risk neutral ($\overline{ror} \in [-1\%, 1\%]$). Of the risk averse subjects, 3 subjects (2% of the total) never took any risk ($\overline{ror} > 100\%$). We did not observe any subject always taking a risk ($\overline{ror} < -32\%$).

Those results are consistent with Holt and Laury (2002), which find that about two-thirds of the subjects in their experiments were risk averse when all prizes are below US$4.00. They note that risk aversion increases when payoffs are scaled up. This explains our higher proportion of risk-averse subjects since the highest possible outcome was 8 Euro in our experiment (plus 3 Euro as show-up fee). We will discuss the dependence of *ror* on the magnitude of the loss c in the lottery in section 3.7.

3.4.2 Privacy preferences

We compute an ***i****ndex of* ***a****ttitude to* ***p****rivacy* ***r****isk* ("IAPR") defined as the value that equates the certainty equivalent x of the lottery and the *expected value* of the lottery, $y \cdot p + (y - IAPR) \cdot (1 - p)$, whereby the value of privacy is IAPR. The IAPR is therefore an implicit monetary measure of the (dis)utility of privacy risk:

$$IAPR = \frac{y - x}{1 - p} \tag{3.2}$$

This value represents the equivalent in monetary terms of the risk of a "loss of privacy" (*i.e.* personal information disclosure). Positive value of the IAPR can be translated into a dis-utility of the risk of personal information disclosure, while negative value of the IAPR can be attributed to the utility of the risk of personal information disclosure ("privacy exhibitionism"). We draw the reader's attention to the fact that the IAPR is not a monetary equivalent of privacy loss, but of the *risk* of such a loss. In other words, the IAPR takes into account both the value attached to privacy by a subject and his level of aversion to risk. We explain later how we disentangle the two.

We compute an interval estimate of the value of the IAPR as implied by individual switching points in the MPL menus of the privacy task (tab. 3.2). Namely, we use the midpoint of the switching interval as our measurement of x when subjects switched only once, and the mean value between the lower bound of the first switch and the upper bound of the last switch in MPL tables when subjects switched more than once. Tab. 3.2 shows that with our choice of privacy lotteries, we are able to obtain a value of $IAPR$ as long as it is no higher than 150 ECU (15 Euro) and no lower than -100 ECU (-10 Euro).

Of the 148 subjects in our experiment, 49 subjects or about 33% of our sample had a mean value of $IAPR = 5$ ECU, which corresponds to 0.5 Euro. This value corresponds to the mean IAPR for subjects who consistently preferred a safe payoff to the same safe payoff with a risk of privacy disclosure, but switched to the risky option as soon as the lottery outcome exceeded the safe payoff. $IAPR = 5$ ECU is therefore the cut-point separating subjects who liked the opportunity of disclosing their information in at least one table from subjects who disliked doing so on average.

Table 3.2: Interval estimation of $IAPR$, in Experimental Currency Unit (ECU). (1 ECU = 0.1 Euro).

MPL table	Range of safe outcomes (in ECU)	Lottery option	Elicitation interval for the IAPR
5	46 - 56	Get 55, but Pr=0.3 of personal information disclosure	$-3 < IAPR < 30$
6	38 - 68	Get 65, but Pr=0.3 of personal information disclosure	$-10 < IAPR < 90$
7	30 - 80	Get 75, but Pr=0.3 of personal information disclosure	$-17 < IAPR < 150$
8	35 - 65	Get 30, but Pr=0.3 of personal information disclosure	$-100 < IAPR < 0$

In total, 94 subjects (64% of the total) had mean values of IAPR higher than 5 ECU (*privacy protective*), of which 14 never took any privacy risk (IAPR> 150 ECU), 49 subjects (33% of the total) were close to indifferent to the risk of personal information disclosure (IAPR= 5 ECU) and 5 subjects (3% of the total) had a mean value of IAPR lower than 5 ECU (*exhibitionists*). There were no subjects who always chose the risky option (IAPR< -100 ECU). The mean of IAPR for those subjects for which it was measured (90% of the total) was 25 ECU (2.5 Euro).

The majority of our subjects were thus averse to privacy disclosure, a large minority was indifferent and a small minority appeared to enjoy privacy disclosure and was ready to pay for it. This contrasts with WTA and WTP which were all higher than or equal to zero. It might be that subjects did not realize they could express negative values for their WTA or their WTP; future experiments on privacy should be careful to make participants aware that they can also express willingness to pay to disclose personal information rather than assuming that all participants are unwilling to disclose.

With the exception of a few subjects, most of our subjects were not comfortable with personal information disclosure. A substantial number of participants chose safe options in privacy lotteries, demonstrating the presence of privacy concerns. This is because even though synthetically generated personal information can hardly be misused to harm participants after the end of the study, reputation created on the basis of expressed opinions remains even outside of the lab after the experiment. The salience of conformist opinion was increased by presenting opinions along with statistics on the opinion of peers on the same issue. Together with observed diversity of opinions this served to reinforce privacy concern. We indeed observed some degree of nervousness and anxiety for subjects whose information was eventually disclosed to others in the lab. Many participants also mentioned privacy concerns in the open-ended question of the exit survey.

While the majority of people attributed a positive value to personal information and did tend to protect it from disclosure, we found, as a number of studies suggest, that some people, in contrast, wanted to make their personal information and opinions public. Such differences reflect differences in goals, attitudes personality traits and other factors (see Zywica and Danowski, 2008; Krasnova et al., 2009; Ross et al., 2009; Correa et al., 2010). This minority tendency to disclose is consistent with the use of social technologies, such as online social networks, blogs, *etc.*, and could be especially prevalent for the active users of such technologies, extensively present in the population of students, and, consequently, in our sample.[8]

3.5 Are individuals who are more risk-averse also less willing to reveal private information?

To test the first hypothesis stated in section 3.2, we run a first set of interval regression to take account of right-censoring in our data on $\overline{IAPR_i}$. The first set of regressions take the following form:

$$\overline{IAPR_i} = \beta_0 + \beta_1 \cdot \overline{ror}_i + \beta_2 \cdot Shock_i + \beta_3 \cdot Order_i + \beta_4 \cdot Table_k + ... + \epsilon_{ik} \tag{3.3}$$

where $\overline{IAPR_i}$ is average $IAPR$ for individual i across tables $k \in [5, 8]$, except if the individual never switched in any table, in which case we code $\overline{IAPR_i} >$ 150 ECU. $\overline{ror}_i$ is average ror for subject i from his choices in tables $k \in [1, 4]$ – we include in our regressions a dummy equal to 0 if $\overline{ror_i} > 100\%$, 1 else, which we interact with $\overline{ror}_i$. $Shock_i$ takes value 0 for participants assigned to the basic treatment and value 1 for those assigned to the shock treatment; $Order_k$ takes value 0 if monetary task appeared before privacy task, 1 otherwise; $Table_k$ is a control for differences in IAPR across tables.

We also include other variables measuring attitudes to privacy from survey responses. In particular, we use explicit self-reported WTA for privacy disclosure (Q6 in the final questionnaire, appendix B.2) and WTP for privacy protection (Q7). Socio-demographic indicators include gender, age, field of study, level of education, nationality, parents' education, size of the locality (city, town, village. . .) and income level (monthly spending) (Q8 to Q15). Other measures of privacy attitudes include general privacy concern (Q16), experience of privacy invasions (Q21), questions to compute Westin's Privacy Index (Q22, see Westin, 1968), and questions to compute a self-disclosure index (Q30[9]). Based on Fogel and Nehmad (2009), we also asked how subjects deal with private information online (Q17 to Q20, summarized in an index of online information revelation[10]),

[8] Only about 5% of our participants indicated they were not members of any online social network.

[9] The self-disclosure index is computed as sum of a, c, d, f, and i minus b, e, g, h and j.

[10] The index of "online information revelation" is computed using a single-factor measurement model whereby answers to questions Q17 and Q19 are modeled as ordered logit and answers to questions Q18 and Q20 are modeled as logit.

the number of their offline and online friends (Q23 and Q25), the online social network they use (Q24)[11], and their privacy settings in online networks (Q26 to Q29, summarized in index "privacy online"[12]). We also collected other variables related to privacy concerns in the experiment: number of known other participants (Q3), trust in the use of information by the experimenter (Q5), and an index of *conformity* to the opinion of others in the preliminary questionnaire (average percentage of participants who agree with one's opinion). This latter variable is designed to take account of a possible exacerbated privacy concern for those subjects who know or think that their opinion does not fit with the majority. Finally, we elicit general and domain specific risk attitude (Q31 and Q32, summarized in index "risk"[13]) and level of trust in others (Q33 to Q37, summarized in index "trust"[14]).

We also run a second set of regressions using a panel random-effects interval-data regression model where we input the number of safe choices made in privacy risk tables as our dependent variable, and the average number of safe choices made in monetary risk tables instead of $\overline{ror}_i$ as an independent variable. This regression method allows us to take account of censoring below and above if a subject always chose option A or option B in a given MPL table. This second set of regressions takes the following form:

$$safe\_privacy_{ik} = \beta_0 + \beta_1 \cdot \overline{safe\_monetary_i} + \beta_2 \cdot Shock_i + \beta_3 \cdot Order_i + \\ + \beta_4 \cdot Table_k + ... + \epsilon_{ik} \quad (3.4)$$

whereby $safe\_privacy_{ik}$ is the number of safe choices made by individual i in table k, $k \in [5, 8]$ and $\overline{safe\_monetary_i}$ is the average number of safe choices made by individual i in tables k, $k \in [1, 4]$.

Tab. B.11 shows results of various specifications for our first set of regressions (appendix B.7). Tab. B.12 shows results of various specifications for the second set of regressions (appendix B.7). We first discuss the impact of risk and privacy preferences on the decision to incur privacy risk before discussing treatment and order effects.

Our regressions show that the ror measure of aversion to risk in monetary tasks is a significant positive predictor of the $IAPR$ measure of aversion to risk in privacy task. We find the same positive significant relation between the number of safe choices made in monetary lotteries and in privacy lotteries. This supports the first part of our first hypothesis: subjects who are more risk-averse in monetary lotteries are also more risk-averse in privacy lotteries.

[11] 80% indicated Facebook, so the variable is coded as 1 for Facebook, 0 for others.

[12] In the "privacy online" index, Q26 to Q29 are coded as 1 if a subject answered 1 in Q26, 1 or 2 in Q27, 1 in Q28 and 1 in Q29 , and 0 otherwise. We then sum those variables.

[13] The "risk index" is computed using a single-factor measurement model whereby answers to questions Q31 and Q32 are modeled as ordered logit.

[14] The trust index is computed using a single-factor measurement model whereby answers to questions Q33, Q34 and Q35 are modeled as ordered logit and answers to questions Q36 and Q37 are modeled as logit.

We also find that WTA and WTP both predict higher IAPR, whereby the IAPR increases by an average of 0.5 ECU (= 0.05 Euro) for every Euro increase in WTA, and by an average of 2 ECU (= 0.20 Euro) for every Euro increase in WTP. There is therefore a relation between our implicit measure of privacy risk aversion and explicit measures of valuations for privacy, but that relation is rather weak. The weak relation with WTA shows that WTA is not only overstated[15] but also less tightly related with observed behavior than WTP. Another factor that independently relates to the IAPR is the experience of a violation of privacy in the past (Q21). Westin's fundamentalists have significantly higher values of the IAPR under some specifications. The general question about privacy concern Q16 is significantly related to the IAPR in the panel random-effect regressions. The results of our regressions show that none of the socio-demographic questions influences the IAPR or the number of safe choices made, except being a foreigner (non-Italian), which increases the number of safe choices made in privacy lotteries. Those additional findings support our second hypothesis: subjects who express more concern for privacy and/or express higher values for protecting their private information are also less likely to take the risk of having to reveal private information.

In terms of contributions of privacy and monetary risk attitudes to explaining attitudes to privacy risk, the McFadden's pseudo R^2 of our full model is 10.7% for IAPR regressions and 8.9% for safe choice regressions.[16] Of this, about 40% is contributed by measures of risk attitude in monetary lotteries, 40% by the combination of WTA and WTP, and the rest by survey measures of privacy attitudes and socio-demographic variables.[17]

Overall, therefore, attitudes to privacy risk do not appear to fundamentally differ from attitudes to monetary risk: 1) subjects who express more concern for privacy and who are ready to pay more to protect it or who require more money to reveal it, are also less likely to take a risk in privacy lotteries, in the same way as they are less likely to take risk when potential losses are higher. 2) subjects who are more risk averse when faced with monetary lotteries are also more risk averse when faced with privacy lotteries, which is also consistent with privacy having a monetary equivalent. We discuss this hypothesis further in section 3.6, where we measure the effect of our shock treatment and how the order of elicitation affects preferences.

While we do find some correlation between WTA/WTP and the IAPR or

[15]WTA observed in our experiment is 8 times higher than WTP, which is in line with the 7.17 mean WTA/WTP ratio found by Horowitz and McConnell (2002) across 45 studies about a variety of goods. Grossklags and Acquisti (2007) reports ratios between 4 and 36 times depending on type of information (quiz results, weight, favorite vacation destination, and number of sexual partners). For a review, see Horowitz and McConnell (2002); Roth (2006).

[16]McFadden's pseudo R^2 compare the log-likelihood LL_0 of the null model with only an intercept to the log-likelihood LL_{Full} of the full model: $R^2 = 1 - {}^{LL_{Full}}/_{LL_0}$.

[17]We measure contribution as the percentage of the difference in log-likelihood between the null model and the full model that is achieved by a model with the respective variable alone. An alternative measure of contribution is by considering by how much the log-likelihood decreases when removing one variable. In that case, the contribution of the measure of monetary risk attitude is lower.

number of safe choices in privacy tasks in our regressions, and while this correlation is robust to a number of regression specifications, this pattern holds only in the aggregate. Indeed, we find large divergences between WTA and WTP at the individual level, and wide discrepancies between those values and the IAPR. Different measures of aversion to private information disclosure are certainly not always consistent at the individual level; many individuals behave in ways that are inconsistent with their expressed WTA and WTP. In other words, implicit and explicit measures do not always coincide, even though they do correlate at the aggregate level.

Our results should not be interpreted to mean that subjects who are more risk-averse have a higher utility for personal information. Indeed, $IAPR$ is only a way to index decisions in privacy lotteries, and does not take into consideration risk-tolerance levels. It is not an estimate of a subject's utility of personal information. It reflects both value for personal information and readiness to take risk in lotteries (and possibly some other factors, *e.g.,* loss aversion). The true value for privacy of a risk averse subject is lower than $IAPR$. We offer later a method to retrieve monetary values of privacy corrected for risk aversion but we first check that the relation between monetary and privacy risk aversion is robust across treatments.

3.6 Treatment effects

Before trying to retrieve monetary values of privacy from decisions under risk, we need to check that behavior under privacy risk is of the same nature as behavior under monetary risk. Indeed, it is not at all obvious that subjects deal with privacy risk in the same way as with monetary risk. We were particularly concerned about the issue of control over private information. Prior research has indeed identified control or the lack thereof as an important driver of risk attitudes and behaviors (Weinstein, 1984; Harris, 1996; Slovic, 2000; Nordgren et al., 2007). It could be that privacy has worth only in so far as one has got control over its probability of disclosure. Suppose indeed that you know that whatever you do, your private information is at risk of being revealed. Then you have to mentally anticipate this disclosure and prepare for it. Avoiding having to anticipate privacy disclosure may be a large part of why some people are averse to privacy risk. Therefore, forcing our subjects to have to anticipate privacy disclosure might reduce their willingness to protect their information. One can make opposite arguments however. Some subjects may have a maximum allowable level of risk they are ready to take with their private information, and may therefore take more care to protect their information if it is already under risk so as not to exceed this threshold. In order to settle the question, we therefore test the effect of depriving participants of control over their personal information in a complementary treatment.

As an additional robustness check we also tested whether the order of elicitation of attitudes to monetary and privacy risk had an effect on subjects' decisions. Indeed, asking subjects first about monetary risk and then about privacy risk may induce them to think of a loss of privacy in the same way as of a monetary loss, so we need to check whether the correlation between attitudes to monetary and privacy risk also holds when privacy risk attitudes are elicited first.

3.6.1 Loss of control

Control over personal information flows is often seen in the privacy literature as a prerequisite for privacy protection (*e.g.,* Kang, 1998; Solove, 2006). A Madden and Rainie (2015) survey found that while 74% of Americans thought that control over personal information is very important, only 9% of them believed they had such control. Online social networks have moved towards providing a more granular control over privacy settings to their users, which seems to be a response to their privacy concerns. However, a "control paradox" arises, whereby higher perceived control over personal information can lead to a decline in concerns about privacy and an increase in information disclosure, even when the associated risks are very high (John et al., 2011b; Brandimarte et al., 2013). Using dynamic lotteries in a lab experiment, Feri et al. (2016) found that subjects were less likely to disclose their personal information after receiving a breach notification, which jeopardized their personal information. Unlike Feri et al. (2016), which focused on the dynamic effect of breach notifications, we focus on differences between treatments with and without the possibility of a privacy shock. Furthermore, instead of measuring subjects' willingness to sell their personal information, we look into their willingness to take the risk of revealing it.

In our experiment, we therefore test the effect of reducing control over the release of personal information by introducing the possibility of a "privacy shock" (probabilistic disclosure of personal information, even when the participant always chose the safest option in privacy lotteries). We compare treatments with the possibility of such a shock to treatments where participants can guarantee through their decisions that no revelation of private information will occur. We look at the number of safe choices and IAPR taking into account all individual decisions and controlling for individual effects. Neither the panel regression of the number of safe choices nor the regression on IAPR in appendix B.7, nor the tests on the cumulative distribution function of safe choices and IAPR by treatment show any treatment effect.[18]

Thus, we conclude that the introduction of a privacy shock does not lead people to change their attitude towards protection of personal information. In

[18] Tests of the difference in the number of safe choices: two-sample Wilcoxon rank-sum test: Prob $> |z| = 0.84$; t-test: $\Pr(|T| > |t|) = 0.9996$; Kolmogorov-Smirnov equality-of-distributions test: corrected p-value is 0.99; ANOVA: coefficient is -0.0002, $P>|t|=1.00$; Kruskal-Wallis equality-of-populations rank test: Prob=0.84. N=592 (268 and 324 in shock and basic treatments, respectively). Statistical power is 0.05.
Tests of the difference in $IAPR$: two-sample Wilcoxon rank-sum test: Prob $> |z| = 0.41$; t-test: $\Pr(|T| > |t|) = 0.91$; Kolmogorov-Smirnov test: corrected p-value is 0.79; ANOVA: coefficient is -0.30, $P>|t|=0.91$; Kruskal-Wallis rank test: Prob=0.41. N=375 (171 and 204 in shock and basic treatments, respectively). Estimated statistical power is 0.05.

other words, even when complete control over personal information is taken away, whereby one introduces a risk of information disclosure that is independent of one's choices, people keep on considering the level of risk that remains under their control in the same way as if they had full control over whether to incur this risk. This finding suggests that the utility function for privacy risk is inelastic with regard to the level of control over personal information disclosure. Depriving people of control over their personal data has a negligible effect on their willingness to protect it from disclosure.

3.6.2 Order effect

Theories of selective information processing state that focus on a primary task reduces attention to a secondary task (Kahneman, 1973). If the monetary lotteries are presented prior to the privacy ones, subjects could keep their focus on monetary outcomes and calculation of expected values, "learned" from the monetary lotteries, when making decisions in the privacy lotteries. In this case, due to selective attention, the emphasis on monetary values could drive away attention to the evaluation of personal information utility. The latter could be even perceived as irrelevant for decision-making when the monetary context is set up in advance (Broadbent, 1957, 1982; Pashler and Sutherland, 1998; Dukas, 2004; Lachter et al., 2004).

In contrast, playing privacy lotteries first could draw more attention to the personal information (dis)utility. Moreover, the time delay between generation of personal information by answering the sensitive questions, and putting these responses under risk of disclosure, is shorter when the privacy lotteries are played right after the completion of the preliminary questionnaire rather than in the second part of the experiment. Adjerid et al. (2013) found that even 15-second delay between demonstration of privacy notice and disclosure decisions was sufficient to distract participants and mute the risk perception.

To test the order effect we consider the number of safe choices and IAPR across different ordering of monetary and privacy tasks in the experiment. Statistical tests and cumulative distribution function show a significant order effect in privacy task: subjects made more safe choices in the privacy lotteries and had higher IAPR when privacy tasks appeared before the monetary tasks.[19] A similar effect is observed also in terms of the percentage of subjects who took only safe alternative in privacy tables (20% when privacy task first *vs.* 12%

[19]Tests of the difference in the number of safe choices: two-sample Wilcoxon rank-sum test: Prob $>$ |z| = 0.01; t-test: $Pr(T < t) = 0.01$; Kolmogorov-Smirnov equality-of-distributions test: corrected p-value is 0.04; ANOVA: coefficient is 0.77, P>|t|=0.02; Kruskal-Wallis equality-of-populations rank test: Prob=0.01. N=592 (312 and 280 in monetary and privacy tasks first conditions, respectively). Estimated statistical power is 0.66.
Tests of the difference in IAPR: two-sample Wilcoxon rank-sum test: Prob $>$ |z| = 0.028; t-test: $Pr(T < t) = 0.03$; Kolmogorov-Smirnov equality-of-distributions test: corrected p-value is 0.10; ANOVA: coefficient is 5.53, P>|t|=0.06; Kruskal-Wallis equality-of-populations rank test: Prob=0.03. N=375 (206 and 169 in monetary and privacy tasks first conditions, respectively). Estimated statistical power is 0.45.

when monetary task first).[20] The proportion of people who behaved as if they had close to zero value for privacy – switching to the risky choice as soon as its payoff was higher than the safe choice – was significantly lower when privacy lotteries appeared first than when monetary lotteries appeared first (25% *vs.* 36%, respectively). [21] One of the possible explanations is that doing the monetary task first could prime people to consider personal information in the same terms as money, while doing the privacy task first induces people to think about personal information in a different way that translates into more privacy risk aversion.

While cumulative distribution function and statistical tests show that values of the IAPR are greater when privacy task appears first, coefficients on this condition dummy in regressions (appendix B.7) are not consistently significant. However, we find that the relation between the IAPR and *ror* is stronger when privacy task appeared first (fig. B.3b).[22] This suggests that in the condition where the privacy task was presented before the monetary one, the decision in privacy task was largely driven by risk attitudes, while risk aversion played a smaller role when the privacy task was presented after the monetary task. In the latter case, the attention of participants may have been drawn to monetary outcomes rather than to risk evaluation or privacy concerns.

3.7 Implicit monetary values for privacy

Various studies suggest strong relation of risk attitudes and individual decisions across different contexts (such as work, personal finance, and health (Soane and Chmiel, 2005), food risky for health (Lusk and Coble, 2005), and insurances (Petrolia et al., 2013; Menapace et al., 2016)). Dohmen et al. (2011) find the evidence that the general willingness to take risk explains about 60% of variability in risk attitudes, while only about 5% variability is captured by the domain-specific risk preferences (car driving, sports and leisure, health, financial matters, and career). Although, for the best of our knowledge, there is no empirical evidence of correlation between risk tolerance levels elicited in gamble task to the context of privacy, we showed that risk attitudes are of a similar nature in the monetary and the privacy context; subjects react to the risk of a privacy loss in ways that are consistent with privacy loss being of the same nature as a monetary loss. We can therefore estimate monetary values of privacy by taking account of the risk tolerance level that was elicited in the monetary task. Since we elicited both monetary and privacy risk aversion, we can disentangle risk preferences from the (dis)utility of personal information disclosure.

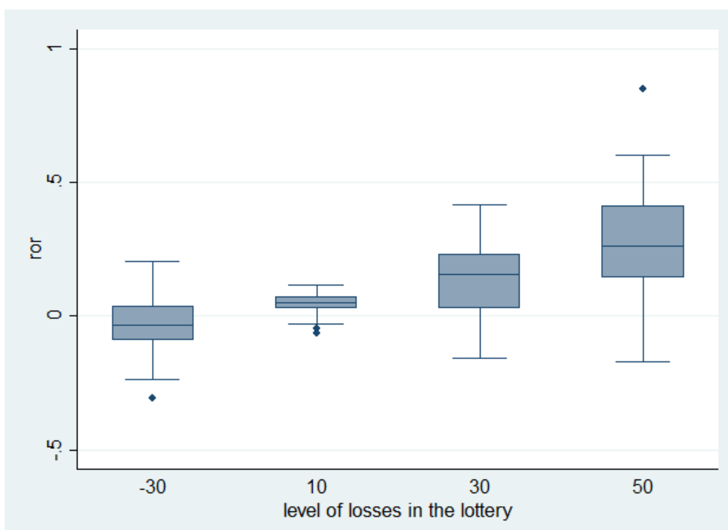
[20] Excluding MPL table 4, proportion test $\Pr(Z < z) = 0.01$. Pearson chi2(1) = 5.32 ($\Pr = 0.021$). Estimated power is 0.63.

[21] Two-sample test of proportions: $\Pr(Z > z) = 0.00$. Estimated power is 0.83.

[22] Results from regressions confirm that there is no significant relation between ror and the IAPR if monetary lotteries are presented first, while the relation is significant if privacy lotteries are presented first.

Willingness to take risk depends both on how large relative variation in payoffs are in the lottery (standard deviation σ) and on whether the lottery involves gains or losses. In our menu of lotteries, there is a linear relation between σ and $|c|$ – standard deviation in lottery outcomes increases linearly with the absolute value of the loss/gain c – so we can simply replace the relation between ror and σ with a relation between ror and $|c|$ to take into account standard deviation. As for differences in risk attitude when faced with gains *vs.* when faced with losses, a visual inspection of individual ror as a function of c reveals that ror increases with c, the size of the loss (fig. 3.2). A regression of ror on c and $|c|$, whereby $ror(c) = ror_\alpha \cdot |c| + ror_\beta \cdot c$ gives out an estimate of average $ror_\alpha = 1.96‰$ and $ror_\beta = 3.47‰$ ($N = 534$, $R^2 = 57\%$, $F(2, 532) = 353$, $p < 1‰$).[23] This implies that subjects require a rate of return that increases by $3.47 + 1.96 = 5.43‰$ for each additional unit of loss ($c > 0$), and *decreases* by $3.47 - 1.96 = 1.51‰$ for each additional unit of gain ($c < 0$). Subjects are thus risk-loving, on average, when faced with a lottery that involves gains, while they are risk averse when faced with a lottery that involves losses of the same magnitude. This is predicted by prospect theory when, as in our case, probabilities of loss or gain are low (Tversky and Kahneman, 1992).

Figure 3.2: Boxplot of the individual level of ror by level of loss in monetary lotteries.



We can therefore obtain per-subject estimates of ror for different possible levels of valuation of privacy by estimating individual by individual a regression

[23]We do not want to allow for a constant in such regressions as then we would have $ror(0) \neq 0$ which implies requiring a return on an asset with no risk. Allowing a constant in our regressions does not change the results and the constant is not significantly different from zero.

of the form $ror(c) = ror_\alpha \cdot |c| + ror_\beta \cdot c$.[24] Consider thus an individual with level of risk aversion represented by the couple (ror_α, ror_β). Suppose this individual is indifferent between safe payoff x and a risky option with payoff y and a probability $1-p$ of personal information disclosure. Then, for this individual, privacy loss is equivalent to a monetary loss of magnitude v_p such that $x \cdot (1 + ror_\alpha \cdot |v_p| + ror_\beta \cdot v_p) = y \cdot p + (y - v_p) \cdot (1-p)$.

Solving for v_p, the implied equivalent monetary loss (or gain) from personal information disclosure corrected with risk attitude is thus[25]:

$$v_p = \frac{y-x}{1-p+x\cdot(ror_\alpha + ror_\beta)} \text{ if } v_p > 0 \tag{3.5}$$

$$v_p = \frac{y-x}{1-p+x\cdot(-ror_\alpha + ror_\beta)} \text{ if } v_p < 0 \tag{3.6}$$

Our method for correcting the IAPR with *ror* to obtain a value of privacy v_p has the advantage of being able to easily condition the level of *ror* on the level of v_p. The value of v_p can differ significantly from the value of the IAPR . Indeed, unwillingness to take a risk of personal information disclosure may be due to either high risk aversion or high dis-utility from such disclosure. We saw that aversion to privacy risk and aversion to monetary risk were positively related, but as fig. B.2 shows, there are a number of individuals with high monetary risk aversion and low privacy risk aversion, and vice-versa. There are many participants with the same aversion to privacy risk but they have distinct risk attitudes, and therefore will have different values of v_p. A subject who values privacy positively but has a high level of risk aversion (high ror_α and ror_β) will have lower value of v_p than a subject who also values privacy positively but is less risk-averse.

Using formula 3.5, we obtain values of average individual v_p that are distributed more smoothly than the uncorrected average IAPR (fig. B.1). Average individual v_p is 1.50 Euro, compared with an average WTP of 1.92 Euro and an average WTA of 16.12 Euro. The distribution of values of v_p is also more consistent with those of WTP than with those of WTA.

We identify 4 individuals with negative values of privacy, compared with 126 with positive values for privacy. This does not include the 14 individuals who never took privacy risks, neither does this include 3 individuals who never took monetary risk, both type of individual for whom only a lower bound (resp. upper bound) estimate of v_p is available. Our estimates of v_p show that there are individuals with implicit negative values of privacy (see fig. B.1). This implies that enjoying revelation of private information may occur, at least in our sample and given our method for generating private information.

[24] This is subject however to having individual estimates of *ror* when the lottery implies a gain and when the lottery implies a loss. If not, then either ror_α or ror_β is set equal to 0.

[25] Those formulas imply that it is possible theoretically that we would obtain values of v_P that are positive if we assume v_p is positive, and negative if we assume that v_p is negative. This happens however only for one subject with our data. In that case, we assume that v_p is positive if $y - x$ is positive and vice-versa.

We find no significant correlation between estimates of v_p, those of WTA and those of WTP. The lack of consistency is surprising given that WTA and WTP were elicited after the experiment was finished, so the subjects had had time to evaluate their attitude to privacy. This underlines again the difficulty for people to give direct monetary equivalents for something like privacy which is not generally experienced as being a tradable good. Welfare evaluations of the impact of privacy losses should therefore not be based on valuations derived from direct elicitation of WTP or WTA payment for private information disclosure. Rather, they should be elicited, like in this experiment, indirectly and in such a way that one can retrieve implicit monetary equivalents from similar decisions involving money rather than privacy. We showed in this experiment that at least in the case of information about opinion on sensitive social topics, people seemed to behave when faced with privacy risk in similar ways as they behaved when faced with monetary risk, thus allowing us to compute monetary equivalents of the value of privacy.

We test our estimates of v_p for robustness by measuring risk aversion levels when assuming that our subjects have a CRRA utility function $u(x) = x^r$ and when assuming that our subjects have a CARA utility function $u(x) = 1 - e^{-\alpha x}$. Given a risk aversion coefficient r in the CRRA case, we obtain $v_p = y - (\frac{x^r - p \cdot y^r}{1-p})^{1/r}$. Given a risk aversion coefficient α in the CARA case, we obtain $v_p = y - \ln(\frac{e^{-\alpha x} - p \cdot e^{-\alpha y}}{1-p})^{-1/\alpha}$. Estimates of v_p with those alternative methods are consistent and very highly correlated with our main estimates.

3.8 Conclusion

We presented novel methods for (1) the generation of privacy concerns in a laboratory setting, (2) the elicitation of the (dis)utility of the risk of personal information disclosure, and (3) the disentangling of risk attitudes from privacy attitudes in decisions involving risk of personal information revelation. We found that implicit and explicit measures of the value of privacy differ substantially. Implicit elicitation technique may help to avoid the expressions of socially desirable answers and beliefs, thus revealing the true preferences of the subjects.

We ran a laboratory experiment with 148 subjects and collected 13,024 observations on choices made between sure monetary payoff and lotteries of two types. Lotteries in monetary domain served to elicit monetary risk preferences, while privacy lotteries elicited willingness to protect from disclosure the personal information that included name, surname, photo, and responses to the preliminary questionnaire about opinion on sensitive and socially relevant topics. Additionally we manipulated the order in which monetary and privacy lotteries were presented to the subjects and the level of control they had over personal information by introducing privacy shocks in the form of a chance of eventual personal information disclosure regardless of the choices made. We applied the prior incentive system to provide transparent and tangible economic incentive (Johnson et al., 2015a).

We found a consistent positive relationship between monetary and privacy risk aversion. This supports the idea that willingness to protect personal information may be driven at least in part by risk aversion rather than only, or even mainly, by differences in values for personal information and privacy attitudes. This may also serve as an explanation of the privacy paradox: when people take risks of personal information revelation even though they express high levels of privacy concerns, this may be due to their high level of risk tolerance rather than being an inconsistency.When asked about their privacy attitude or WTP/WTA for privacy, people respond both based on their value for privacy and their attitude to risk. This is why it is very important to know individual attitude to risk in order to properly evaluate individual attitudes to privacy as such.

We also found that the introduction of a privacy shock, under which personal information was compromised independently of the choices of participants, did not affect the willingness to take risk in privacy tasks. Taking control over privacy away from participants did not either encourage or discourage them from protecting it. Finally, we found qualified support for the existence of an order effect, whereby presenting privacy lotteries prior to monetary ones leads to a more privacy-protective behavior. We interpret this to mean that either privacy attitudes are affected by an immediacy effect (subjects make more privacy protective decisions right after answering private questions), or that thinking about financial risk first leads subjects to think of privacy in monetary terms, thus possibly leading to less risk averse behavior. This finding may find application in the creation of privacy policies, in the timing of privacy decisions and in the design of personal data marketplaces. Emphasizing monetary benefits before asking for privacy-related choices may lead to higher disclosure. Conversely, asking for privacy choices first may result in more protection of one's personal data.

Our proposed elicitation method can be applied to different types of private data that could allow future research to compare the inferred (dis)utility of privacy risk in various domains, for example, towards financial, health, social network and other personal information. The method is also applicable to various types of privacy risk, *e.g.,* sharing data with third parties, hacking attacks, use of personal information for marketing purposes and unsolicited advertising, *etc.*

To the best of our knowledge, ours is the first work trying to separate two determinants of attitudes to privacy risk - basic willingness to disclose personal information and risk aversion. We found many risk-averse people who were comparatively ready to take risks with personal information disclosure. This indicates that they were actually quite willing to disclose this information. Indeed, for a risk-averse person to take a decision that is risky for his privacy, the willingness to disclose his personal information should be high enough to outweigh his general tendency to avoid risk. In contrast, people with a high value for personal information (and thus large dis-utility from its disclosure) should love risk enough to "convince" them to expose their privacy to risk. This observation suggests that many choices that aim to protect privacy may be mistakenly attributed to a concern about personal information disclosure, while in fact being driven by general risk aversion. Such mistaken attribution would lead to inaccurate evaluations of the (dis)utility of personal information disclosure. Indeed, correction with risk attitude in our study reveals the existence of some people who are "privacy exhibitionists", *i.e.* subjects with negative utility for personal information. This subset of people does not appear when considering other measures. Privacy researchers should make sure that their methods to elicit attitudes to privacy risk allow for the expression of preferences consistent with privacy exhibitionism.

Appendices

Appendix A

Factors Influencing the Perceived Websites' Privacy Trustworthiness and Users' Purchase Intentions

A.1 Questionnaire items

Construct	Sub-construct	Variable: Trustworthiness perceptions	Variable: Purchase intentions	Item
Security		ST	SP	
		ST1	SP1	The Company has published assurances from independent third parties and their icons on Website
		ST2	SP2	The Company has a password-composition policy, *i.e.* it imposes requirements for password creation on its Website (*e.g.*, length, obligatory including of numbers and letters of different register, *etc.*)
		ST3	SP3	Green padlock icon is present in the location bar to the left of the Web address verifying that the Company's Website uses Extended Validation certificate
		ST4	SP4	Several payment options are available on the Website of the Company (like credit cards, PayPal, Web wallets, bank transfer, *etc.*)
Privacy		PT	PP	
	Collection	LT	LP	
		LT1	LP1	Notifications, banners and ads about products you searched once on the Company's Web site appear when you are visiting other Website
		LT2	LP2	In order to recommend products/services that you can be interested in, the Company's Website asks about your tastes and preferences
		LT3	LP3	In order to recommend products/services that you can be interested in, the Company's Website uses specific technologies to track your behavior and figure out your preferences

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Construct	Sub-construct	Variable		Item
		Trustworthiness perceptions	Purchase intentions	
		LT4	LP4	The Company allows an access to the content of its Website without registration but requires to provide some personal information in order to place an order and purchase products and services from it
		LT5	LP5	The Company requires to provide some personal information in order to get an access to its Website and contents
		LT6	LP6	The details of user's credit card are remembered by the Company's Website for future purchases
		LT7	LP7	The user's address is remembered by the Company's Website for future deliveries
	Control	NT	NP	
		NT1	NP1	The Company's Website (not browser) asks you to remember your login and password in order to enter quickly next time you will visit it without necessity to type
		NT2	NP2	The Company's Website asks your permission for using you current location
		NT3	NP3	The Company's Website allows you registration via other Web sites (*e.g.*, sign up through linking Facebook or Google profile)
		NT4	NP4	The Company's Website's mobile application can't be installed without permission to access some information (*e.g.*, location, device model, profile, activity history, *etc.*)
		NT5	NP5	The Company's Website's mobile application can't be installed without permission to access some information but you are allowed to partially edit the list of permissions

continued on the next page

Construct	Sub-construct	Variable: Trustworthiness perceptions	Variable: Purchase intentions	Item
	Awareness	AT	AP	
		AT1	AP1	The Company's Website clearly explains how customer's information is going to be used and how it will be shared with other companies and third parties
		AT2	AP2	Informational text about use of cookies is clearly present on the Website as a fixed banner
		AT3	AP3	The general privacy policy is clear and easy to understand
Reputation		RT	RP	
	Background	BT	BP	
		BT1	BP1	Key names and photos of real people behind the Company's Web site are shown
		BT2	BP2	The Company's Website carries products/services with reputable brand names
		BT3	BP3	The Company runs business and has its Website for many years
		BT4	BP4	The background of the Company (history from establishing to nowadays) is described on its Website
	Feedback	FT	FP	
		FT1	FP1	The Company has both good and bad feedback, positive and negative reviews from other users and customers on independent Websites and forums
		FT2	FP2	The Company has both good and bad feedback, positive and negative reviews from other users and customers on its Website
		FT3	FP3	The Company has a high ranking in traditional media (TV, radio, printed editions, *etc.*)

continued on the next page

Construct	Sub-construct	Variable		Item
		Trustworthiness perceptions	Purchase intentions	
		FT4	FP4	The Company has a high ranking in online sources (like BizRate, Consumer reports Online eRatings, *etc.*)
		FT5	FP5	The Company has good feedback and positive reviews from other users and customers on its Website
		FT6	FP6	There is a widget on the Company's Website that tells you which people with whom you are friends on Facebook like this Company and its products/services
Website quality		QT	QP	
		QT1	QP1	The visual appearance and manner of the Company's Web site is not professional (amateur looking)
		QT2	QP2	The Company has broken links and typographical errors on its Website
		QT3	QP3	The Company's Website has suspicious banners, ads and links to third party unrelated Websites

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A.2 Final questionnaire and summary statistics

1. What do you think was the purpose of the experiment? (Max 200 words)
2. How difficult was it for you to make a decision? (1= Not Difficult at All (7%), 2 = Not Very Difficult (49%), 3 = Somewhat Difficult (39%), 4 = Very Difficult (5%))
3. What is your gender (1 = Male (37%), 2 = Female (63%))
4. What is your age? (1 = < 18 years (0%), 2 = 18-25 years (0%), 3 = 26-30 years (1%), 4 = 31-35 years (10%), 5 = 36-40 years (44%), 6 = > 41 years (45%))
5. What is your field of study? (1= Social Sciences (Economics, Sociology, Low, etc.) (29%); 2 = Technical sciences (Informatics, Engineering, Architecture, etc.) (32%), 3 = Medical sciences (Medicine, Nursing, Pharmaceutics, etc.) (2%), 4 = Humanities and Arts (Literature, Languages, Arts, etc.) (23%), 5 = Natural Sciences (Chemistry, Physics, Mathematics, etc.) (14%), 6 = Education science and pedagogics (0%), 7 = Agriculture (Agriculture, Veterinary, etc.) (0%), 8 = Other Applied Sciences (specify) (0%)).
6. What is the highest level of education you have completed up to now? (1 = High school diploma or less (36%), 2 = Secondary school (17%), 3 = Bachelor's Degree (38%), 4 = Master's Degree (7%), 5 = Doctoral degree (3%), 6 = Other (specify) (0%))
7. What is your nationality? (1= Italian (99%), 2 = Other (1%))
8. Did your parents complete their secondary education? (1 = None of my parents completed secondary education (26%), 2 = Only one of my parents completed secondary education (37%), 3 = Both parents completed secondary education (37%))
9. Where did you live for most part of your life? (1 = Village with < 1 000 inhabitants (7%), 2 = Town with 1,000 – 10,000 inhabitants (16%), 3 = City with 10 001 – 100,000 inhabitants (32%), 4 = City with 100,000 – 1,000,000 inhabitants (43%), 5 = Big city with population > 1 million inhabitants (2%))
10. What is your main source of income? (1 = Job (full-time) (67%), 2 = Job (part-time), 3 = Scholarship (27%), 4 = Parents (5%), 5 = Spouse (1%), 6 = Other relatives or members of family (0%), 7 = Bank loan (0%), 8 = Other (specify) (0%))
11. How much do you spend every month? (including food, clothes, rent, utilities (heating, water), education, entertainment, etc.) (1 = < 500 Euro (2%), 2 = 501-800 Euro (21%), 3 = 801-1200 Euro (32%), 4 = 1201-2000 Euro (31%), 5= > 2000 Euro (15%), 6 = Prefer not to answer (0%))

12. Which programming language are you able to use (more than one answer is allowed)? (1 = Java / Java Script, 2 = C / C++, 3 = Python, 4 = Ruby, 5 = Matlab, 6 = HTML, 7 = R, 8 = I do not know any programming language, 9 = Other[1])

13. Since how many years are you using Internet? (1 = Less than 1 year (0%), 2 = 1-2 years (2%), 3 = 3-5 years (7%), 4 = 5-8 years (11%), 5 = More than 8 years (80%))

14. How many hours do you spend online per week? (Mean = 17.96; sd = 15.26; min = 0; max = 70)

15. How often do you use the Internet for each of the following purposes[2]:

    (a) Entertainment
    (b) Educational
    (c) Work-related research
    (d) Personal finance (banking, stock trading)
    (e) Current events (news, sports, weather)
    (f) Travel-related (research, reservations)
    (g) Product information gathering
    (h) Making purchases from online merchants
    (i) Communicating with others (chat/email/Social Network)
    (j) Other (specify)

    (1 = Often; 2 = Sometimes; 3 = Never)

16. How often do you buy products/services online that cost[3]:

    (a) Less than 50 Euro
    (b) 50-100 Euro101-300
    (c) Euro301-500 Euro
    (d) 501-1000 Euro
    (e) More than 1000 Euro

[1] 63% of respondents do not know any programming language. Respondents who knew at least one, on average, know 2 programming languages.

[2] Using single-factor measurement model we computed two indices: a) an index of using Internet for utilitarian purposes (mean = -6.32e-09; sd = 0.15, min = -0.33; max = 0.28; Cronbach's alpha = 0.4625) based on the responses about the use of Internet for educational, work-related, personal finance, and product-information gathering purposes; and b) an index of using Internet for hedonic purposes (mean = 1.66e-09; sd = 0.19, min = -0.42; max = 0.30; Cronbach's alpha = 0.6110) based on the responses about the use of Internet for entertainment, current events, travel-related, making purchases, and communication purposes.

[3] Using single-factor measurement model we computed an "Online shopping frequency" index (mean = -2.29e-09; sd = 0.56, min = -0.37; max = 3.30; Cronbach's alpha = 0.8854) based on the responses.

(1 = Never; 2 = Once a year; 3 = Several times a year; 4 = Once a month; 5= Several times a month; 6 = Once a week; 7 = Several times a week)

17. "I prefer to buy products and services from physical store rather than online". (1 = I totally disagree (10%), 2 = I somewhat disagree (47%), 3 = I somewhat agree (31%), 4 = I totally agree (12%))

18. What agencies that specialize on users' online privacy and security are you familiar with? More than one answer is allowed. (1 = VeriSign (44% are familiar), 2 = Entrust (15%), 3 = TRUSTe (35%), 4 = BBBOnline (Better Business Bureau Online) (1%), 5 = AIPC Webtrust (1%), 6 = WebAssured (8%), 7 = Pretty Good Privacy (6%), 8 = Thawte (8%), 9 = Other (specify) (29%)[4])

19. Do you recognize the label that represents the compliance of the web site with the Extended Validation certificate? (1 = No (55%), 2 = Yes (45%))

20. Please, explain what does the Extended Validation certificate mean? (1 = specify; 2 = I do not know what it is[5])

21. Please, explain what do cookies mean? (1 = specify; 2 = I do not know what it is[6])

22. Are you concerned about your privacy online? (1 = Not concerned at all (6%), 2 = Somewhat unconcerned (28%), 3 = Somewhat concerned (56%), 4 = Very concerned (10%))

23. Rate your level of concern over the following Internet issues[7]:

    (a) It's too hard to use
    (b) It's too hard to find what I want
    (c) Someone could be monitoring what I do online
    (d) It's too expensive Pornography is too easily accessible
    (e) It's too cluttered
    (f) It's too slow
    (g) I get too much junk eMail
    (h) My personal information will be stolen
    (i) Someone will misuse the personal information I give them
    (j) Information will be censored

[4]Sixty-nine percent of the respondents were familiar with 1 agency, 20% - with 2 agencies, 8 % - with 3 agencies, 3 % - with 4 agencies, and 1% - with 5 agencies.

[5]55% of the respondents understood the meaning of EV certificate correctly.

[6]69% of the respondents understood the meaning of cookies correctly.

[7]Using single-factor measurement model we computed an index of privacy being a motivation for concern related to the use of Internet (mean = -1.69e-09; sd = 0.39, min = -1.1; max = 0.52; Cronbach's alpha = 0.7820) based on the responses about statements 3, 9 and 10 of the Q23.

(k) Other (specify)

(1 = Not at all concerned; 2 = Somewhat unconcerned; 3 = Somewhat concerned; 4 = Very concerned)

24. If asked to provide personal information, how often (in percentage) do you refuse to give the requested personal information / leave the web site? (mean = 45.09%; sd = 31.18; min =0%; max = 100%)

25. If you do provide personal information to web sites, how often (in percentage) do you provide false information (if at all)? (mean = 9.77%; sd = 16.26; min =0%; max = 90%)

26. If you have refused to disclose personal information or given falsified information, how important to you were the following issues[8]:

    (a) I am unfamiliar with how the technology works
    (b) I am unfamiliar with the company/individual running the site
    (c) The company/individual running the site does not have good reputation
    (d) I don't trust the company/individual running the site
    (e) The site does not disclose how they plan to use my information
    (f) The value I will receive from the site is not worth the information I give
    (g) I generally prefer to be anonymous
    (h) They asked for particularly sensitive pieces of information
    (i) I am concerned that the information will be intercepted or stolen
    (j) It takes too much time to fill out the forms
    (k) I am concerned I will receive junk mail if I give my home address
    (l) I am concerned I will receive junk email if I give my email address
    (m) I am concerned I will receive junk SMS/calls if I give my (mobile) telephone number
    (n) Other (specify)

    (1 = Not one of my reasons; 2 = Not very important; 3 = Somewhat important reason; 4 = Very important reason)

[8]Using single-factor measurement model we computed two indices: a) an index of privacy concern being a reason for not providing or providing falsified information (mean = 0.008; sd = 0.47, min = -1.97; max = 0.49; Cronbach's alpha = 0.7980) based on the responses about statements 5-9; and b) an index of trust issues being a reason for not providing or providing falsified information (mean = -0.003; sd = 0.41, min = -1.68; max = 0.28; Cronbach's alpha = 0.9015) based on the responses about statements 2-4 in Q26.

27. How willing are you to provide personally identifiable information and demographics to web sites? (1 = Not willing at all (3%), 2 = Not very willing (63%), 3 = I am indifferent (19%), 4 = I would not mind (11%), 5 = Very willing (3%))

28. Would you be more willing to provide personally identifiable information and demographics for online advertising purposes if the website compensated you for your information? (1 = No (62%), 2 = Yes (38%))

29. How willing are you to provide information about your tastes, interests and preferences without personal identification to web sites? (1 = Not willing at all (5%), 2 = Not very willing (28%), 3 = I am indifferent (28%), 4 = I would not mind (30%), 5 = Very willing (9%))

30. Would you be more willing to provide personal information about your tastes, interests and preferences for online advertising purposes if the website compensated you for your information? (1 = No (31%), 2 = Yes (69%))

31. Have you personally experienced incidents whereby your personal information was used by some company or e-commerce website without your authorization? (1 = No (66%), 2 = Yes (34%))

32. Have you personally been the victim of what you felt was an invasion of privacy? (1 = No (57%), 2 = Yes (43%))

33. Please indicate to which extend you (dis)agree with the following statements[9]:

    (a) Consumers have lost all control over how personal information is collected and used by companies

    (b) Most businesses handle the personal information they collect about consumers in a proper and confidential way

    (c) Existing laws and organizational practices provide a reasonable level of protection for consumer privacy today

    (1 = Strongly Agree; 2 = Somewhat agree; 3 = Somewhat disagree; 4 = Strongly disagree)

34. If you are a member of an online social network, which do you use the most actively? (more than one answer is allowed) (1 = Facebook (56% use it), 2 = Google + (19%), 3 = Twitter (9%), 4 = My Space (0%), 5 = Instagram (10%)6 = Other (specify) (9%), 7 = I am not a member of any online social network (29%))

[9] We computed a Westin's Privacy index (Westin, 1968): 1 = Unconcerned (0-1 privacy concerned answers); 2 = Pragmatists (2 privacy concerned answers); 3 = Fundamentalists (3 privacy concerned answers). Statement 1 of Q33 was reversed coded.

35. How many connections do you have on Facebook? (1 = < 50 (20%), 2 = 51-100 (15%), 3 = 101-200 (9%), 4 = 201-300 (4%), 5 = 301-500 (9%), 6 = 501-700 (1%), 7 = 701-1000 (1%), 8 = 1001-2000, 9 = > 2000 (0%), 10 = I do not have a profile on Facebook (39%))

36. What do you use as your user name in Facebook? (1= Real name (57%), 2 = Pseudonym, and nobody knows who I am in real life (3%), 3 = Pseudonym, but everybody knows who I am in real life (0%), 4 = I do not have Facebook account (39%))

37. What do you use as profile picture in your primary social network? (1 = Real photo of me (42%), 2 = Real photo of me with other person/people (6%), 3 = Photo of other person or celebrity (1%), 4 = Photo/image of non human being (5%), 5 = No photo at all (4%), 6 = I do not have a Facebook account (39%), 7 = Other (3%))

38. What are your privacy settings on Facebook? (1 = Public. Everybody can get access to my profile and read my entries (7%); 2 = Private. Only my friends can get access to my profile and read my entries (36%); 3 = My profile and entries are mostly public and partially private (3%); 4 = My profile and entries are mostly private and partially public (12%); 5 = I have different accounts for public and private entries (0%); 6 = I do not have a Facebook account (39%); 7 = Other (please describe in details) (3%))

39. Did you ever change your privacy settings on Facebook? (1 = Never (20%); 2 = I changed privacy settings on Facebook immediately after registration (20%); 3 = I changed privacy settings on Facebook several times (20%); 4 = I changed privacy settings on Facebook after someone misused my personal information (1%); 5 = I do not have a Facebook account (39%); 6 = Other (please describe in details) (0%))

40. What is your favorite movie? (1 = Specify (85%); 2 = I do not wish to say (15%))

41. What is your favorite book? (1 = Specify (82%); 2 = I do not wish to say (18%))

42. What is your favorite sport? (1 = Specify (89%); 2 = I do not wish to say (11%))

43. What is your hobby? (1 = Specify (91%); 2 = I do not wish to say (9%))

44. Imagine that 2 people do the same job in the same company. Both have the same qualification, but the person A works more productively than person B. Is it fair that person A gets a larger remuneration? (1 = Yes, it's fair (94%); 2 = No, it's unfair (6%))

45. "In general, one can trust people ..." (1 = I totally agree (4%); 2 = I somewhat agree (43%); 3 = I somewhat disagree (50%); 4 = I totally disagree (3%))

46. "Nowadays one cannot rely on anyone ..." (1 = I totally agree (7%); 2 = I somewhat agree (67%); 3 = I somewhat disagree (23%); 4 = I totally disagree (3%))

47. "When dealing with strangers it's better to be careful before trusting them..." (1 = I totally agree (11%); 2 = I somewhat agree (52%); 3 = I somewhat disagree (37%); 4 = I totally disagree (0%))

48. Do you think that the majority of people... (1 = "... would exploit you if they had an opportunity ..." (45%); 2 = "... would try to be fair to you ... " (55%))

49. Do you think that people most of the times... (1 = "... try to be considerate of others" (72%); 2 = "... follow their own interests" (28%)[10])

[10] Using single-factor measurement model we computed a "trust disposition" index based on the responses to Q45-49 (mean = 2.13e-09; sd = 0.42; min = -0.91; max = 0.83; Cronbach's alpha = 0.7582).

A.3 Summary statistics of values

Table A.1: Summary statistics of values of trustworthiness perceptions

Variable	Mean	Median	Std. Dev.	Variance	Min	Max
QT3	2.97	3	1.98	3.92	1	11
QT1	3.30	3	1.85	3.43	1	10
QT2	3.31	3	2.17	4.70	1	12
LT6	3.69	3	2.66	7.05	1	11
LT1	3.91	4	2.31	5.33	1	10
NT4	4.16	4	2.64	6.96	1	12
FT6	4.53	4	2.63	6.93	1	12
NT2	4.74	4	2.65	7.03	1	12
NT3	4.90	5	2.60	6.76	1	12
LT2	4.92	5	2.57	6.59	1	11
LT3	5,03	4	2.64	6.99	1	11
LT5	5.13	5	2.66	7.05	1	12
LT7	5.40	5	2.73	7.44	1	12
LT4	5.41	6	2.74	7.49	1	12
NT5	5.61	6	2.66	7.06	1	12
NT1	5.69	6	2.82	7.94	1	12
FT1	5.81	6	2.41	5.81	1	12
FT2	6.07	6	2.53	6.42	1	12
AT2	6,18	6	2.84	8.06	1	12
BT2	6.52	6	2.73	7.47	1	12
BT4	6.57	6	2.65	7.02	1	12
FT5	6.80	7	2.77	7.68	1	12
FT4	6.84	7	2.87	8.26	1	12
BT1	7.06	7	2.90	8.38	1	12
FT3	7.12	7	2.82	7.93	1	12
ST4	7.22	7	3.01	9.06	1	12
BT3	7.46	8	2.80	7.84	1	12
ST1	7.53	8.5	3.12	9.72	1	12
ST3	7.57	8	2.81	7.87	1	12
AT3	7.75	8	3.04	9.26	1	12
AT1	7.84	8	2.91	8.50	1	12
ST2	7.93	8.5	2.85	8.15	1	12

Table A.2: Summary statistics of values of purchase intentions

Variable	Mean	Median	Std. Dev.	Variance	Min	Max
QP3	2.83	2	2.06	4.26	1	12
QP1	3.04	3	1.85	3.43	1	10
QP2	3.26	3	2.30	5.27	1	12
LP6	4.61	4	3.13	9.80	1	12
LP1	4.73	5	2.54	6.47	1	11
NP4	4.92	5	2.82	7.94	1	12
LP5	5.83	6	2.74	7.49	1	12
NP2	5.97	6	2.78	7.73	1	12
LP4	6.05	7	2.92	8.51	1	12
NP3	6.08	6	2.78	7.71	1	12
FP1	6.20	6	2.64	6.95	1	12
LP2	6.24	6	2.79	7.79	1	12
NP5	6.26	6	2.74	7.51	1	12
FP6	6.48	6.5	2.98	8.87	1	12
FP2	6.53	6	2.72	7.41	1	12
NP1	6.59	7	2.91	8.47	1	12
LP3	6.59	7	2.83	8.00	1	12
AP2	6.61	7	2.87	8.22	1	12
LP7	6.69	7	2.97	8.83	1	12
BP4	7.20	7	2.47	6.08	1	12
BP1	7.58	8	2.68	7.20	1	12
FP4	7.79	8	2.87	8.25	1	12
SP1	7.80	8	3.19	10.16	1	12
SP2	7.81	8	2.77	7.70	1	12
SP3	7.86	8	2.80	7,82	1	12
AP3	7.90	8.5	2.84	8.09	1	12
AP1	7.91	8	2.82	7.93	1	12
FP5	7.95	9	3.07	9.45	1	12
BP2	8.03	8	2.77	7.68	1	12
FP3	8.26	9	3.00	9.02	1	12
SP4	8.47	9	3.02	9.14	1	12
BP3	8.53	9	2.68	7.21	1	12

A.4 Confirmatory factor analysis of the measurement model

Table A.3: CFA of the measurement model of trustworthiness perceptions

Construct	Sub-construct	Variable	Factor loading	Uniqueness	Cronbach's α
Security		ST	-	-	0.8952
		ST1	0.7607	0.4213	
		ST2	0.8676	0.2473	
		ST3	0.7988	0.3619	
		ST4	0.8263	0.3172	
Privacy		PT	-	-	0.8688
	Collection	LT	0.8808	0.2243	0.8569
		LT1	0.5403	0.7081	
		LT2	0.6878	0.5269	
		LT3	0.7007	0.5091	
		LT4	0.6884	0.5261	
		LT5	0.7830	0.3869	
		LT6	0.6496	0.5780	
		LT7	0.6924	0.5206	
	Control	NT	0.8562	0.2669	0.8415
		NT1	0.8548	0.2693	
		NT2	0.6850	0.5308	
		NT3	0.7157	0.4878	
		NT4	0.6448	0.5842	
		NT5	0.8113	0.3417	
		NT6	0.7032	0.5055	
	Awareness	AT	0.6990	0.5114	0.8615
		AT1	0.6876	0.5271	
		AT2	0.8604	0.2597	
		AT3	0.7949	0.3681	
		AT4	0.7417	0.4498	

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Construct	Sub-construct	Variable	Factor loading	Uniqueness	Cronbach's α
Reputation		RT			0.9094
	Background	BT	0.8744	0.2354	0.9030
		BT1	0.8743	0.2357	
		BT2	0.8268	0.3164	
		BT3	0.8518	0.2745	
		BT4	0.7742	0.4007	
		BT5	0.8525	0.2733	
	Feedback	FT	0.8744	0.2354	0.8990
		FT1	0.8743	0.2357	
		FT2	0.7830	0.3869	
		FT3	0.7273	0.4711	
		FT4	0.8488	0.2795	
		FT5	0.6288	0.6047	
		FT6	0.7950	0.3679	
		FT7	0.8447	0.2864	
Website quality		QT	-	-	0.6458
		QT1	0.4686	0.7805	
		QT2	0.6943	0.5180	
		QT3	0.5821	0.6611	

end of the table

Table A.4: CFA of the measurement model of purchase intentions

Construct	Sub-construct	Variable	Factor loading	Uniqueness	Cronbach's α
Security		SP	-	-	0.9030
		SP1	0.7419	0.4497	
		SP2	0.8297	0.3116	
		SP3	0.8263	0.3173	
		SP4	0.8642	0.2531	
Privacy		PP	-	-	0.8659
	Collection	LP	0.8671	0.2481	0.8748
		LP1	0.6758	0.5432	
		LP2	0.7736	0.4015	
		LP3	0.7250	0.4744	
		LP4	0.7247	0.4748	
		LP5	0.7093	0.4969	
		LP6	0.6419	0.5880	
		LP7	0.6875	0.5273	
	Control	NP	0.8048	0.3523	0.8437
		NP1	0.8027	0.3557	
		NP2	0.6973	0.5137	
		NP3	0.7415	0.4502	
		NP4	0.6251	0.6093	
		NP5	0.7797	0.3921	
		NP6	0.7301	0.4670	
	Awareness	AP	0.7428	0.4482	0.8598
		AP1	0.7377	0.4558	
		AP2	0.8675	0.2474	
		AP3	0.7884	0.3784	
		AP4	0.7343	0.4608	

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Construct	Sub-construct	Variable	Factor loading	Uniqueness	Cronbach's α
Reputation		RP			0.9334
	Background	BP	0.9058	0.1796	0.9113
		BP1	0.9059	0.1794	
		BP2	0.8440	0.2877	
		BP3	0.8236	0.3216	
		BP4	0.8471	0.2824	
		BP5	0.8418	0.2913	
	Feedback	FP	0.9058	0.1796	0.8785
		FP1	0.9059	0.1794	
		FP2	0.7214	0.4796	
		FP3	0.6891	0.5252	
		FP4	0.7841	0.3852	
		FP5	0.6604	0.5639	
		FP6	0.7635	0.4170	
		FP7	0.8069	0.3489	
Website quality		QP			0.6895
		QP1	0.5677	0.6777	
		QP2	0.7473	0.4416	
		QP3	0.5594	0.6871	

end of the table

A.5 Structural equation model estimation results

Table A.5: Measurement model SEM estimation results

Latent variable	Item variable	Stand. path coefficient	p-value	AVE	CR	R-sq
Security						
ST	ST1	0.757	0.000	0.681	0.895	0.573
	ST2	0.892	0.000			0.795
	ST3	0.816	0.000			0.666
	ST4	0.830	0.000			0.689
SP	SP1	0.740	0.000	0.680	0.894	0.548
	SP2	0.841	0.000			0.708
	SP3	0.831	0.000			0.690
	SP4	0.880	0.000			0.774
Privacy Collection						
LT	LT1	0.579	0.000	0.448	0.849	0.335
	LT2	0.739	0.000			0.547
	LT3	0.705	0.000			0.498
	LT4	0.609	0.000			0.371
	LT5	0.753	0.000			0.566
	LT6	0.553	0.000			0.306
	LT7	0.719	0.000			0.516
LP	LP1	0.709	0.000	0.488	0.869	0.503
	LP2	0.806	0.000			0.650
	LP3	0.733	0.000			0.537
	LP4	0.616	0.000			0.379
	LP5	0.708	0.000			0.502
	LP6	0.583	0.000			0.340
	LP7	0.713	0.000			0.509
Control						
NT	NT1	0.592	0.000	0.523	0.844	0.351
	NT2	0.722	0.000			0.522
	NT3	0.671	0.000			0.451
	NT4	0.877	0.000			0.769
	NT5	0.722	0.000			0.522
NP	NP1	0.596	0.000	0.511	0.838	0.355
	NP2	0.761	0.000			0.579
	NP3	0.667	0.000			0.445
	NP4	0.813	0.000			0.661
	NP5	0.717	0.000			0.514

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Latent variable	Item variable	Stand. path coefficient	p-value	AVE	CR	R-sq
Awareness						
AT	AT1	0.976	0.000	0.707	0.887	0.952
	AT2	0.709	0.000			0.503
	AT3	0.817	0.000			0.667
AP	AP1	0.955	0.000	0.688	0.867	0.913
	AP2	0.707	0.000			
	AP3	0.808	0.000			0.652
Reputation						
Background						
BT	BT1	0.856	0.000	0.702	0.904	0.732
	BT2	0.850	0.000			0.723
	BT3	0.765	0.000			0.585
	BT4	0.876	0.000			0.767
BP	BP1	0.850	0.000	0.722	0.912	0.722
	BP2	0.839	0.000			0.704
	BP3	0.856	0.000			0.732
	BP4	0.855	0.000			0.731
Feedback						
FT	FT1	0.771	0.000	0.610	0.903	0.595
	FT2	0.722	0.000			0.522
	FT3	0.789	0.000			0.623
	FT4	0.863	0.000			0.745
	FT5	0.859	0.000			0.739
	FT6	0.660	0.000			0.435
FP	FP1	0.700	0.000	0.554	0.880	0.489
	FP2	0.615	0.000			0.378
	FP3	0.755	0.000			0.569
	FP4	0.854	0.000			0.730
	FP5	0.814	0.000			0.662
	FP6	0.704	0.000			0.495
Website quality						
QT	QT1	0.504	0.000	0.452	0.696	0.254
	QT2	0.903	0.000			0.815
	QT3	0.535	0.000			0.287
QP	QP1	0.556	0.000	0.517	0.743	0.309
	QP2	1.000	0.000			1.000
	QP3	0.492	0.000			0.242

end of the table

Note: R-squared is equal to Bentler-Raykov squared multiple correlation coefficient.

Table A.6: Structural model SEM estimation results

Latent variable	Item variable	Stand. path coefficient	p-value	AVE	CR	R-sq
Trust (T)	ST	0.899	0.000	0.618	0.912	0.808
	QT	0.224	0.039			0.050
	BT	0.905	0.000			0.819
	FT	0.863	0.000			0.745
	AT	0.869	0.000			0.755
	NT	0.744	0.000			0.553
	LT	0.771	0.000			0.595
	Control variables:					
	Q3: Female	-0.054	0.000			
	Q4: Age	-0.214	0.019			
	Q9: Urban	0.021	0.828			
	Q10: Income source	-0.230	0.019			
	Q11: Spending	-0.065	0.498			
	Q12: Programming languages	0.070	0.489			
	Q13: Internet experience	0.233	0.022			
	Q16: Online shopping frequency	0.040	0.698			
	Q17: Online shopping preference	-0.073	0.480			
	Q18: Familiarity with privacy agencies	0.014	0.889			
	Q20: Correct explanation for EV	-0.136	0.157			
	Q21: Correct explanation for cookies	0.038	0.703			
	Q22: General privacy concern	-0.170	0.053			
	Q27: Willingness to reveal PII	0.059	0.553			
	Q32: Privacy invasion	-0.041	0.690			
	Q33: Westin's privacy index	-0.174	0.065			
	Q35: Number of Facebook connections	-0.599	0.000			
	Q36: Name in Facebook	0.376	0.006			
	Q49: Index of trust disposition	-0.027	0.789			

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Latent variable	Item variable	Stand. path coefficient	p-value	AVE	CR	R-sq
Purchase intention (P)	SP	0.942	0.000	0.664	0.925	0.887
	QP	0.126	0.296			0.016
	BP	0.929	0.000			0.863
	FP	0.910	0.000			0.829
	AP	0.902	0.000			0.814
	NP	0.761	0.000			0.580
	LP	0.810	0.000			0.656
	Control variables:					
	Q3: Female	0.011	0.819			
	Q4: Age	-0.136	0.129			
	Q9: Urban	-0.075	0.422			
	Q10: Income source	-0.191	0.052			
	Q11: Spending	-0.042	0.651			
	Q12: Programming languages	0.090	0.358			
	Q13: Internet experience	0.289	0.002			
	Q16: Online shopping frequency	0.031	0.751			
	Q17: Online shopping preference	-0.132	0.183			
	Q18: Familiarity with privacy agencies	0.012	0.904			
	Q20: Correct explanation for EV	-0.091	0.357			
	Q21: Correct explanation for cookies	-0.008	0.936			
	Q22: General privacy concern	-0.187	0.028			
	Q27: Willingness to reveal PII	0.112	0.237			
	Q32: Privacy invasion	0.044	0.660			
	Q33: Westin's privacy index	-0.152	0.094			
	Q35: Number of Facebook connections	-0.459	0.002			
	Q36: Name in Facebook	0.174	0.196			
	Q49: Index of trust disposition	-0.039	0.696			

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A.6 Goodness of fit, correlation, and covariance

Table A.7: Goodness of fit test results

	Absolute fit indices		Incremental fit indices	
	RMSEA	SRMR	CFI	TLI
Acceptable values	≤ 0.08	≤ 0.08	≥ 0.90	≥ 0.90
Source	Browne et al. (1993)	Hu and Bentler (1999)	Hair et al. (2010)	Hu and Bentler (1999)
Measurement model				
Security	0.057	0.029	0.994	0.989
Collection	0.084	0.082	0.958	0.941
Control	0.108	0.073	0.955	0.924
Awareness	0.080	0.016	0.996	0.982
Background	0.076	0.028	0.989	0.979
Feedback	0.105	0.055	0.953	0.928
Website quality	0.026	0.031	0.999	0.997
Structural model	0.082	0.092	0.922	0.893

Table A.8: Covariance matrix

	ST	QT	BT	FT	AT	NT	LT	SP	QP	BP	FP	AP	NP	P
ST														
QT	-0.052													
BT	0.067	-0.054												
FT	0.197	-0.058	0.307											
AT	0.125	-0.005	-0.025	0.177										
NT	0.089	0.058	0.141	0.328***	0.098									
LT	0.200	0.070	0.348**	0.426***	0.459	0.459***								
SP	1.023***													
QP		0.909***						0.072						
BP			0.707***					-0.193	0.049					
FP				0.402***				-0.168	0.080	0.203				
AP					0.801***			-0.153	0.030	0.143	0.063			
NP						0.529***		-0.136	0.035	0.241	0.323**	0.082		
LP							0.365***	-0.172	-0.007	0.147	0.319*	0.093	0.456***	
T														0.931***

*p-value <0.10; **<0.05; ***<0.01

Table A.9: Correlation matrix

	ST	QT	AT	NT	LT	FT	BT	SP	QP	AP	NP	LP	FP	BP
ST	1.000													
QT	0.122	1.000												
AT	0.835***	0.105	1.000											
NT	0.630***	0.256***	0.578***	1.000										
LT	0.640***	0.365***	0.620***	0.790***	1.000									
FT	0.796***	0.286***	0.768***	0.685***	0.786***	1.000								
BT	0.830***	0.155*	0.753***	0.664***	0.727***	0.852***	1.000							
SP	0.949***	0.124	0.777***	0.551***	0.539***	0.717***	0.760***	1.000						
QP	0.057	0.922***	0.110	0.155*	0.290***	0.256***	0.103	0.077	1.000					
AP	0.844***	0.137	0.914***	0.512***	0.539***	0.716***	0.734***	0.876***	0.105	1.000				
NP	0.675***	0.200**	0.551***	0.747***	0.622***	0.6013***	0.604***	0.697***	0.154*	0.643***	1.000			
LP	0.655***	0.308***	0.564***	0.525***	0.712***	0.649***	0.610***	0.683***	0.262***	0.660***	0.805***	1.000		
FP	0.800***	0.251***	0.7208***	0.513***	0.607***	0.808***	0.712***	0.847***	0.235**	0.818***	0.736***	0.803***	1.000	
BP	0.861***	0.166*	0.7457***	0.562***	0.587***	0.776***	0.880***	0.890***	0.125	0.851***	0.727***	0.728***	0.866***	1.000

*p-value <0.10; **<0.05; ***<0.01

A.7 Summary of the hypotheses test results

Hypothesis	Description	Result
H1a	Privacy -> Trust:	
	AT -> T	Supported ($p < 0.001$)
	NT -> T	Supported ($p < 0.001$)
	LT -> T	Supported ($p < 0.001$)
H1b	Privacy -> Purchase intentions:	
	AP -> P	Supported ($p < 0.001$)
	NP -> P	Supported ($p < 0.001$)
	LP -> P	Supported ($p < 0.001$)
H2a	Security -> Trust:	
	ST -> T	Supported ($p < 0.001$)
H2b	Security -> Purchase intentions:	
	SP -> P	Supported ($p < 0.001$)
H3a	Website quality -> Trust:	
	QT -> T	Supported ($p < 0.05$)
H3b	Website quality -> Purchase intentions:	
	QP -> P	Not supported
H4a	Reputation -> Trust:	
	BT -> T	Supported ($p < 0.001$)
	FT -> T	Supported ($p < 0.001$)
H4b	Reputation -> Purchase intentions:	
	BP -> P	Supported ($p < 0.001$)
	FP -> P	Supported ($p < 0.001$)
H5a	FT1 > FT2	Not supported
	FP1 > FP2	Not supported
H5b	FT1 < FT5	Supported ($p < 0.001$)
	FT2< FT5	Supported ($p < 0.001$)
	FP1 < FP5	Supported ($p < 0.001$)
	FP2< FP5	Supported ($p < 0.001$)
H5c	FT3 > FT4	Not supported
	FP3 > FP4	Supported ($p < 0.05$)
H5d	LT4 > LT5	Not supported
	LP4 > LP5	Not supported
H5e	LT2 > LT3	Not supported
	LP2 > LP3	Not supported
H5f	LT1 < LT3	Supported ($p < 0.001$)
	LP1 < LP3	Supported ($p < 0.001$)
H5g	NT4 < NT5	Supported ($p < 0.001$)
	NP4 < NP5	Supported ($p < 0.001$)

continued on the next page

Hypothesis	Description	Result
H6	Trust ~ Purchase intentions:	
	T ~ P	Supported ($p < 0.001$)
	AT ~ AP	Supported ($p < 0.001$)
	NT ~ NP	Supported ($p < 0.001$)
	LT ~ LP	Supported ($p < 0.001$)
	ST ~ SP	Supported ($p < 0.001$)
	QT ~ QP	Supported ($p < 0.001$)
	BT ~ BP	Supported ($p < 0.001$)
	FT ~ FP	Supported ($p < 0.001$)

end of the table

Appendix B

The Relation Between Privacy Protection and Risk Attitudes, with a New Experimental Method to Elicit the Implicit Monetary Value of Privacy

B.1 Preliminary questionnaire on opinions about potentially sensitive and socially relevant topics

This questionnaire is translated from the Italian original. We show options that were offered to participants and the percentage of participants who chose each option.

1. Experimentation of medications on animals can have an important implication for development of drugs for humans and is often distressing and fatal for animals. Are you in favor or against medical experiments on animals? (0. In favor - 72%; 1 Against - 28%)
2. Using genetically modified organisms in agriculture can help to fight hunger in the world and can present a great danger to ecosystem. Are you in favor or against implementation of such agricultural practices? (0. In favor - 46%; 1 Against - 54%)
3. Which of the following is the more appropriate penalty for rape? (0. Death - 1%; 1. Chemical castration - 34%; 2. Life imprisonment - 35%; 3. Prison sentence, less than life imprisonment - 30%)
4. Albeit rare, there are observed cases of serious complications as consequences of vaccination. The choice not to undergo vaccination significantly increases the risk of getting and transmitting potentially dangerous diseases. Are you in favor or against obligatory vaccination? (0. In favor - 83%; 1. Against - 17%)
5. Billions of Euros are spent each year for aerospace research. Do you think that this money should or should not be spent in other way? (0. Should - 52%; 1. Should not - 48%)
6. Would you for any reason read your mate's email, SMS or pose as him/her online, without his/her knowledge and permission? (0. Yes, they shouldn't be keeping secrets anyway - 14%; 1. Yes, I'd be too curious not to - 6%; 2. Yes, if I suspected them of something - 35%; 3. Never - 45%)
7. Do you think it is morally justified or not justified to abort after discovering serious disability in the fetus? (0. Justified - 58%; 1. Not justified - 42%)
8. Are you in favor or against legislation of prostitution? (0. In favor - 82%; 1. Against - 18%)
9. Which of following substances should be prohibited? (More than one answer is allowed) (0. Alcohol - 3%; 1. Tobacco - 7%; 3. Cannabis - 22%; 4. Cocaine - 85%; 5. Acids (LSD, ecstasy, etc.) - 82%; 6. Heroin - 89%; 7. None - 9%)

10. Are you in favor or against adoption of children by homosexual couples? (0. In favor - 56%; 1. Against - 44%)

11. Are you in favor or against the closure of Italian borders as a solution for the problem of illegal immigration? (0. In favor - 25%; 1. Against - 75%)

12. Are you in favor or against euthanasia (i.e. the painless killing of a patient suffering from an incurable and painful disease or in an irreversible coma)? (0. In favor - 84%; 1. Against - 16%)

13. Some people believe that the trails left by aircrafts in the sky contain chemicals that are inserted specifically to influence the population. Do you think this is a plausible theory or not? (0. Plausible - 10%; 1. Not plausible - 90%)

14. Which of the following methods of birth contraception do you consider as the most appropriate? (0. Hormonal (oral pills, implants, injections, patches, etc.) - 26%; 1. Barrier (condoms, cervical caps, diaphragms, sponges with spermicide, etc.) - 67%; 2. Intrauterine devices - 1%; 3. Sterilization (surgical or chemical) - 3%; 4. Behavioral (interrupted intercourse, fertility awareness method based on the menstrual cycle, sexual abstinence) - 2%; 5. None - 1%)

B.2 Final questionnaire

1. What do you think was the purpose of the experiment?
2. How difficult was it for you to make a decision? (1. Very difficult, 2. Somewhat difficult; 3. Not very difficult; 4. Not difficult at all)
3. Please, indicate how many of today's participants you knew before the experiment? If you did not know anybody in the lab please write zero.
4. Do you think that the remuneration for the experiment is appropriate? (1. Yes; 2. No)
5. Do you trust that experimenters will not misuse the personal information you gave in this experiment? (1. Yes; 2. No)
6. Suppose that you do not have to reveal your private information at the end of the experiment, but the experimenter offers you money so that your name, surname, photo, and answers to the preliminary questionnaire are shown to other participants. What is the minimum amount (in Euros) that you would be ready to accept for this?
7. Suppose that you have to reveal your private information at the end of the experiment, but you can pay the experimenter so that your name, surname, photo, and answers to the preliminary questionnaire are not shown to other participants. What is the maximum amount (in Euros) that you would be ready to pay for this?
8. What is your gender? (1. Male; 2. Female)
9. What is your age? (1. $<$ 18 years; 2. 18-25 years; 3. 26-30 years; 4. 31-35 years; 5. 36-40 years; 6. 41-45 years; 7. 46-50 years; 8. 51-55 years; 9. 56-60 years; 10. $>$ 61 years)
10. What is your field of study? (1. Social Sciences (Economics, Sociology, Low, etc.; 2. Technical sciences (Informatics, Engineering, Architecture, etc.); 3. Medical sciences (Medicine, Nursing, Pharmaceutics, etc.); 4. Humanities and Arts (Literature, Languages, Arts, etc.); 5. Natural Sciences (Chemistry, Physics, Mathematics, etc.); 6. Education science and pedagogics; 7. Agriculture (Agriculture, Veterinary, etc.); 8. Other applied sciences (specify)
11. What is the highest level of education you have completed up to now? (1. Secondary education; 2. Bachelor's Degree; 3. Master's Degree; 4. PhD; 5. Other (specify)
12. What is your nationality? (1. Italian; 2. Other (specify))
13. Did your parents complete their secondary education? (1. None of my parents completed secondary education; 2. Only one of my parents completed secondary education; 3. Both parents completed secondary education)

14. Where did you live for most part of your life? (1. Big city with population $>$ 1 million inhabitants; 2. City with 100.001 - 1.000.000 inhabitants; 3. City with 10.001 - 100.000 inhabitants; 4. Town with 1.000 - 10.000 inhabitants; 5. Village with $<$ 1.000 inhabitants)

15. How much do you spend every month? (including food, clothes, rent, utilities (heating, water), education, entertainment, etc.) (1. $<$ 500 Euro; 2. 501-800 Euro; 3. 801-1200 Euro; 4. 1201-2000 Euro; 5. $>$ 2000 Euro; 6. No answer)

16. Are you generally concerned about your privacy? (1. Not concerned at all; 2. Somewhat unconcerned; 3. Somewhat concerned; 4. Very concerned)

17. How willing are you to provide personally identifiable information and demographics to websites in general? (1. Very willing; 2. I would not mind; 3. I am indifferent; 4. Not very willing; 5. Not willing at all)

18. Would you be more willing to provide personally identifiable information and demographics to websites in general if you were compensated for your information? (1. Yes; 2. No)

19. How willing are you to provide information about your tastes, interests and preferences without personal identification to websites in general? (1. Very willing; 2. I would not mind; 3. I am indifferent; 4. Not very willing; 5. Not willing at all)

20. Would you be more willing to provide personal information about your tastes, interests and preferences to websites in general if you were compensated for your information? (1. Yes; 2. No)

21. Have you personally been the victim of what you felt was an invasion of privacy? (1. Yes; 2. No)

22. Please indicate to which extend you (dis)agree with the following statements (1. Strongly agree; 2. Somewhat agree; 3. Somewhat disagree; 4. Strongly disagree):

23. Consumers have lost all control over how personal information is collected and used by companies

24. Most businesses handle the personal information they collect about consumers in a proper and confidential way

25. Existing laws and organizational practices provide a reasonable level of protection for consumer privacy today

26. Currently in your life, how many close friends would you say you have?

27. If you are a member of online social networks, which do you use the most actively? (The online social network chosen in this questions will be called *your primary social network* hereinafter) (1. Facebook; 2. Google +; 3. Twitter; 4. My Space; 5. Instagram; 6. LinkedIn; 7. FourSquare; 8. Other (specify); 9. I am not a member of any online social network)

28. How many connections do you have in your primary social network? (Write zero if you are not a member of any online social network)

29. What do you use as your user name in your primary social network? (1. Real name; 2. Pseudonym, and nobody knows who I am in real life; 3. Pseudonym, but everybody knows who I am in real life; 4. I am not a member of any online social network)

30. What do you use as profile picture in your primary social network? (1. Real photo of me; 2. Real photo of me with other person/people; 3. Photo of other person or celebrity; 4. Photo/image of non human being; 5. No photo at all; 6. I am not a member of any online social network; 7. Other (specify))

31. What are your privacy settings in your primary social network? (1. Public. Everybody can get access to my profile and read my entries; 2. Private. Only my friends can get access to my profile and read my entries; 3. My profile and entries are mostly public and partially private; 4. My profile and entries are mostly private and partially public; 5. I have different accounts for public and private entries; 6. I am not a member of any online social network; 7. Other (please describe in details))

32. Did you ever change your privacy settings in primary social network? (1. Never; 2. I changed privacy settings immediately after registration; 3. I changed privacy settings several times; 4. I changed privacy settings after someone misused my personal information; 5. I am not a member of any online social network; 6. Other (please describe in details))

33. Please, read the following statements and using the scale below rate how accurately each statement describes **you,** as you generally are now, not as you wish to be in the future. Apart from being anonymous, your responses will be kept in absolute confidence. (1. Very Inaccurate; 2. Moderately Inaccurate; 3. Neither Inaccurate nor Accurate; 4. Moderately Accurate; 5. Very Accurate)

    (a) I am open about myself.
    (b) I don't talk a lot.
    (c) I disclose my intimate thoughts.
    (d) I show my feelings.
    (e) I reveal little about myself.
    (f) I talk about my worries.

(g) I bottle up my feelings.
(h) I prefer to deal with strangers in a formal manner.
(i) I act wild and crazy.
(j) I have little to say.

34. How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please, indicate a number on the scale from 0 to 10, where the value 0 means: *Unwilling to take risks* and the value 10 means *Fully prepared to take risk.*

35. In different areas you can behave differently too. How would you assess your risk tolerance with respect to the following areas (please, indicate a number on the scale from 0 to 10, where the value 0 means: *Unwilling to take risks* and the value 10 means *Fully prepared to take risk).*

    (a) in car driving
    (b) in financial matters
    (c) in leisure and sports
    (d) in you professional career
    (e) in your health
    (f) in trusting strangers

36. "In general, one can trust people ..." (1. I totally agree; 2. I somewhat agree; 3. I somewhat disagree; 4. I totally disagree)

37. "Nowadays one cannot rely on anyone ..." (1. I totally agree; 2. I somewhat agree; 3. I somewhat disagree; 4. I totally disagree)

38. "When dealing with strangers it's better to be careful before trusting them..." (1. I totally agree; 2. I somewhat agree; 3. I somewhat disagree; 4. I totally disagree)

39. Do you think that the majority of people... (1. ...would exploit you if they had an opportunity; 2. ...would try to be fair to you)

40. Do you think that people most of the times... (1. ...try to be considerate of others; 2. ...follow their own interests)

B.3 Instructions

The following instructions are for the shock treatment, "privacy task first" condition and are translated from the Italian original.

Welcome to the experiment!

The experiment will last about 60 minutes. Please make sure that you can stay until the end. You will be paid 3 Euros for showing up on time (participation fee). You can earn more money but this depends on the choices you make in this experiment and on chance. It is therefore important that you read the following instructions carefully.

General rules

You are not allowed to communicate with other participants during the experiment. If you have any doubts or questions, please raise your hand. An assistant will then come to you and answer your question privately.

You received an envelope before the experiment. You are not allowed to open it before the end of the experiment. You will have to open it in front of an assistant.

If you do not follow those rules or disturb the experiment in other ways, then we will ask you to leave the room and we will not pay you.

The Experiment

There are two parts in the experiment: the first part is described in a separate sheet now, while you will get the description of the second part only after completing the first task. You will be presented with tables of choices between two options, one of which gives a certain payoff while the other gives an outcome that depends on chance.

Payment

At the beginning of the experiment, you were asked to pick an envelope from a bag. In total there were 112 envelopes. 88 of those envelopes describe a choice situation that you faced during the experiment. If you got one of those envelopes, then you will get the payoff corresponding to the choice you made in the situation described in your envelope. This means that any of your choices during the experiment could be the one that determines your payoff.

The other 24 envelopes give you a payoff that does not depend on your choice (to be described later).

After having completed both tasks your final payoff will be calculated, each ECU earned will be converted into Euro at the rate of 1 euro for 10 ECUs and paid together with the show-up fee (30 ECUs = 3 euros). For example, if you earned 48 ECUs from your decision during the experiment, then you will receive 48+30 ECUs = 78 ECUs =7,8 Euro in cash.

Anonymity

Since your position in the lab corresponds to the number on a ball taken from a box randomly we only know you by the number of your seat and not by your name, surname or other credentials. Thus, we cannot establish any link between your identity and the decisions you made in the lab, unless the outcome of the experiment suggests revelation of your personal information so that we need to check your name and surname from the ID card.

I. First part of the experiment

In the first part of the experiment, you are asked to make choices between two options of the type described in the following table:

Row	Option A	Option B	Choice
1	You get 13 ECUs	You get 35 ECUs but with probability 50% your personal information is revealed to others	
...	...	...	...

Option A guarantees you a certain payoff, while option B is a lottery that gives out a certain amount of ECUs, but implies some probability of having to disclose your name, surname, photo and answers in the preliminary questionnaire (from then on "personal information") to other participants in the room at the end of the experiment.

You will face 44 choice situations of the type described above. In each of those situations, you must choose the option (A or B) that you prefer. Any of those decisions might be the one that determines your payoff.

Random draw

If you chose option B in which your payoff depends on chance, then you will have to toss a 10-sided die. Each side of the die shows a number, between 0 and 90 in steps of 10 (you can check that the die shows all possible numbers, 0, 10, 20, 30, 40, 50, 60, 70, 80, 90). The probability of personal data revelation defined in this option will be compared with the outcome of this toss:

1. If the outcome of the toss is <u>strictly less</u> than the probability of revelation then your information <u>will be</u> disclosed;

2. If the outcome of the toss is <u>more or equal</u> to the _probability of revelation then your information <u>will not be</u> disclosed.

Envelopes

As explained before, you will get a payoff at the end of the experiment that depends on what is in the envelope that you drew at the beginning of the experiment. There were 112 envelopes, of which 68 relate to the first part of the experiment:

a) 44 of the envelopes describe a choice situation from the first part of the experiment. If you drew an envelope from those 44, then it will look as follows:

Option A: You get 13 ECUs Option B: You get 65 ECUs but with probability 50% your personal information will be revealed to others.

Example: If you have chosen the option B in this situation, you will get 35 ECUs. Then if the outcome of the toss is strictly less than 50, your personal information is revealed to others. If the outcome of the toss is more or equal to 50 then your personal information is not revealed to others.

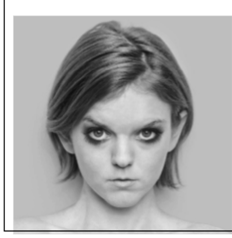
b) 24 of the envelopes say that you have to reveal your personal information to others, independently from your decisions during the experiment. You also then get a certain payoff. The certain payoff may be either 55, 65 or 75 ECUs, and each of those value is as likely as the other. If you drew an envelope from those 24, then it will look as follows:

You get 65 ECUs but your personal information will be revealed to others.

In this case you get 65 ECUs and your personal information will be revealed to others.

Procedure for personal information disclosure

If your personal information has to be disclosed to other participants, then you will be asked to stand in front of the audience in the lab, we will verify your name and surname from your ID card and we will announce your name. Other participants will see on the screen your personal photo and the answers that you gave in preliminary questionnaire, along with a short descriptive comment comparing your answers with the answers of others as in an example below:



Seat #23:
- . . . agrees it is morally justified to abort after discovering serious disability in the fetus, while 36 % of other participants does not agree
- ... is in favor of chemical castration as appropriate penalty for rape, while 87% of other participants did not choose this option
- ...

II. Second part of the experiment

You have finished the first part of the experiment. Now, please, read carefully the description of the second part of the experiment.

In this part you are also asked to make several choices between two options. Consider the following table:

Row	Option A	Option B	Choice
1	You get 37 ECUs	You get 52 ECUs but with probability 50% you lose 14 of those ECUs	
. . .	. . .	. . .	. . .

Option A guarantees you a certain payoff, while option B is a lottery that gives out a certain amount of ECUs, but implies some probability of having to give back some of those ECUs at the end of the experiment. In some tables, option B gives out a certain amount of ECUs and some probability of getting some more ECUs at the end of the experiment.

You must choose the option (A or B) that you prefer.

Random draw

If you chose option B in which your payoff depends on chance, then you will have to toss the 10-sided die. Each side of the die shows a number, between 0 and 90 in steps of 10 (you can check that the die shows all possible numbers, 0, 10, 20, 30, 40, 50, 60, 70, 80, 90). The probability of gaining or losing ECUs that is defined in this option will be compared with the outcome of this toss:

1. If the outcome of the toss is <u>strictly less</u> than the probability of loss/gain then you <u>will lose/gain</u> some ECUs;

2. If the outcome of the toss is <u>more or equal</u> to the probability of loss/gain then you <u>will not lose/gain</u> any ECUs.

Envelopes

As explained before, you will get a payoff at the end of the experiment that depends on what is in the envelope that you drew at the beginning of the experiment. There were 112 envelopes, of which 44 relate to the second part of the experiment. If you drew an envelope from those 44, then it will look as follows:

Option A: You get 37 ECUs Option B: You get 52 ECUs but with probability 50% you lose/gain 14 of those ECUs.

Example: If you chose option B in this case, then you will have to toss the 10-sided die. If the outcome of the toss is strictly less than 50, then you get 52-14=38 ECUs if the loss was indicated or 52+14=66 ECUs if the gain was indicated. If the outcome of the toss is more or equal to 50 then you get 52 ECUs.

B.4 Control questions.

The following control questions are for the shock treatment, "privacy task first" condition and are translated from the Italian original.

We want to make sure that you understand what each option means and let you become familiar with interface of experimental tasks. Therefore, please answer the questions in the examples below. Note that you will not be paid for this.

You will be able to proceed to the next screen only after giving the correct answer. You can try to answer each question several times. If you have questions, please, raise your hand and an assistant will come to you to give you an answer.

Question 1.

Please now make choices for each row of the following table. We remind you that this is for training only so it will not be taken into account when determining your payment.

Row	Option A	Option B	Choice
1	You get 29 ECU	You get 62 ECU but with probability 10% you lose 24 of those ECU	__
2	You get6 ECU	You get 10 ECU but with probability 0% you lose 2 of those ECU	__
3	You get 14 ECU	You get 25 ECU but with probability 50% you lose 5 of those ECU	__

Question 2.

Suppose you are told: " *You get 39 ECU but with probability 10% you lose 25 of those ECU"*. How many ECU will you get?

I will get with probability 90%___________ ECU and with probability 10% ___________ ECU

Correct answer: 39 ECU; 14 ECU.

Question 3.

Suppose you have chosen the following option: *"You get 13 ECU but with probability 70% your personal information is disclosed to others"*. You toss the die and the outcome of the toss is number 70. What is your payoff in this case?

1. I get 13 ECU and the participation fee, my personal information remains anonymous.
2. I get 13 ECU plus the participation fee, but my personal information will be disclosed to other participants in the room in the end of experiment.
3. I get only participation fee.
4. I get nothing.

Correct answer: 2.

Question 4.

Please consider the two options in table below and write down you choice in the box to the right

Row	Option A	Option B	Choice
1	You get 37 ECU	You get 53 ECU but with probability 10% you lose 14 of those ECU	
...	...	...	...

Suppose this choice is the one that is in your envelope, so it determines your payoff.

Given your choice, what will be your payoff (in ECU) if the outcome of the toss of the die is the number 50, and show up fee is 30 ECU?

1. 67 ECU
2. 83 ECU
3. 69 ECU
4. 37 ECU
5. 53 ECU
6. 39 ECU
7. 30 ECU
8. 0 ECU

Correct answer: 1 (if A is chosen), 2 (if B is chosen).

Question 5.

Consider the table below:

Row	Option A	Option B	Choice
1	You get 20 ECU	You get 40 ECU but with probability 20% your personal information is disclosed	A
...	...	...	...

Imagine that you have chosen Option A. Then in the end of the experiment you open your envelope and it is written the following:

You get 40 ECU but your personal information is disclosed to others

What will be your payoff in this case including show up fee of 30 ECU?

1. 20 ECU, personal information remains anonymous
2. 20 ECU, personal information is disclosed

3. 30 ECU, personal information remains anonymous
4. 30 ECU, personal information is disclosed
5. 50 ECU, personal information remains anonymous
6. 50 ECU, personal information is disclosed
7. 40 ECU, personal information remains anonymous
8. 40 ECU, personal information is disclosed
9. 40 ECU, personal information is disclosed if the outcome of the toss of the die is less of equal to 20
10. 70 ECU, personal information remains anonymous
11. 70 ECU, personal information is disclosed
12. 70 ECU, personal information is disclosed if the outcome of the toss of the die is less of equal to 20
13. I get nothing

Correct answer: 11.

B.5 Multiple price list menus of choices

B.5.1 Monetary lotteries (MPL tables 1 to 4)

Table B.1: MPL table 1

Row	Option A	Option B
1	You get 56 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
2	You get 55 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
3	You get 54 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
4	You get 53 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
5	You get 52 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
6	You get 51 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
7	You get 50 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
8	You get 49 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
9	You get 48 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
10	You get 47 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU
11	You get 46 ECU	You get 55 ECU, but with probability 30 % you lose 10 of those ECU

Table B.2: MPL table 2

Row	Option A	Option B
1	You get 68 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
2	You get 65 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
3	You get 62 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
4	You get 59 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
5	You get 56 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
6	You get 53 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
7	You get 50 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
8	You get 47 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
9	You get 44 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
10	You get 41 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU
11	You get 38 ECU	You get 65 ECU, but with probability 30 % you lose 30 of those ECU

Table B.3: MPL table 3

Row	Option A	Option B
1	You get 80 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
2	You get 75 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
3	You get 70 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
4	You get 65 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
5	You get 60 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
6	You get 55 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
7	You get 50 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
8	You get 45 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
9	You get 40 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
10	You get 35 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU
11	You get 30 ECU	You get 75 ECU, but with probability 30 % you lose 50 of those ECU

Table B.4: MPL table 4

Row	Option A	Option B
1	You get 65 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
2	You get 62 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
3	You get 59 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
4	You get 56 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
5	You get 53 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
6	You get 50 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
7	You get 47 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
8	You get 44 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
9	You get 41 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
10	You get 38 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU
11	You get 35 ECU	You get 35 ECU, but with probability 30 % you gain 30 additional ECU

B.5.2 Privacy lotteries (MPL tables 5 to 8)

Table B.5: MPL table 5

Row	Option A	Option B
1	You get 56 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
2	You get 55 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
3	You get 54 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
4	You get 53 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
5	You get 52 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
6	You get 51 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
7	You get 50 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
8	You get 49 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
9	You get 48 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
10	You get 47 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed
11	You get 46 ECU	You get 55 ECU, but with probability 30 % your personal information is disclosed

Table B.6: MPL table 6

Row	Option A	Option B
1	You get 68 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
2	You get 65 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
3	You get 62 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
4	You get 59 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
5	You get 56 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
6	You get 53 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
7	You get 50 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
8	You get 47 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
9	You get 44 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
10	You get 41 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed
11	You get 38 ECU	You get 65 ECU, but with probability 30 % your personal information is disclosed

Table B.7: MPL table 7

Row	Option A	Option B
1	You get 80 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
2	You get 75 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
3	You get 70 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
4	You get 65 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
5	You get 60 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
6	You get 55 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
7	You get 50 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
8	You get 45 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
9	You get 40 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
10	You get 35 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed
11	You get 30 ECU	You get 75 ECU, but with probability 30 % your personal information is disclosed

Table B.8: MPL table 8

Row	Option A	Option B
1	You get 65 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
2	You get 62 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
3	You get 59 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
4	You get 56 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
5	You get 53 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
6	You get 50 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
7	You get 47 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
8	You get 44 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
9	You get 41 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
10	You get 38 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed
11	You get 35 ECU	You get 35 ECU, but with probability 30 % your personal information is disclosed

B.6 Summary statistics

Table B.9: Measures of risk aversion (in %) and (dis)utility of personal information disclosure (in Euros)

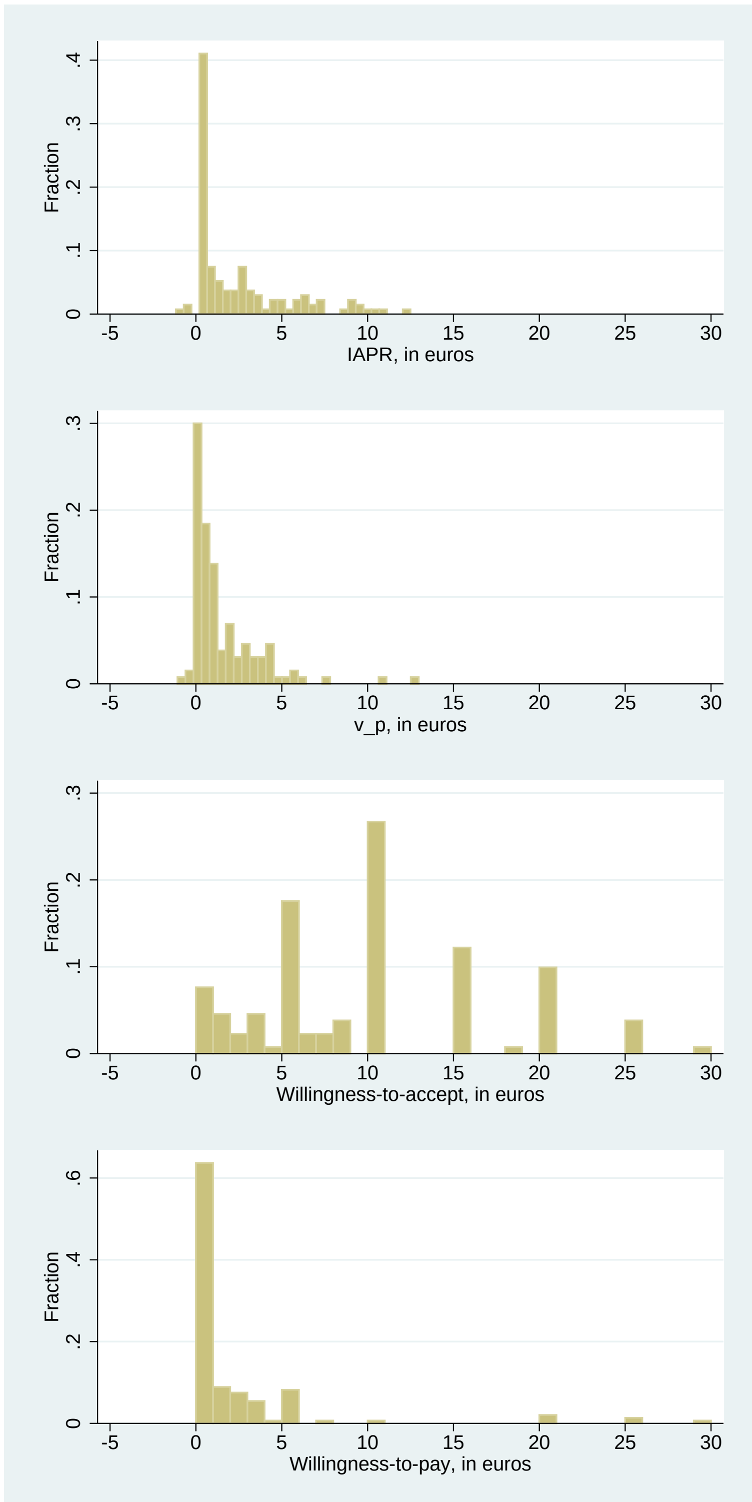
	$\overline{ror}$	$\overline{IAPR}$	$\overline{v_P}$	WTA	WTP
Min	-11%	-1.17	-3.54	0	0
Max	41%	12.50	10.85	200	30
Mean	11%	2.52	1.17	16.12	1.92
Std. deviation	10%	2.89	2.08	25.33	4.85
N	145	134	130	144	146

Note: Outliers for WTA and WTP (values that are 2 standard deviations away from the mean) are excluded. Before exclusion WTA and WTP range between 0 Euro and 1000 Euro.

Table B.10: Explicit and implicit measures of (dis)utility of personal information disclosure and privacy risk, in Euros.

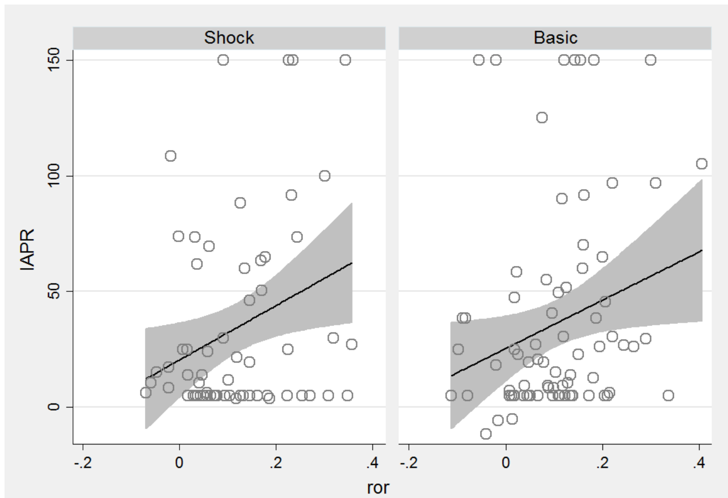
	By treatment		By condition		Total
	Basic	Shock	Monetary first	Privacy first	
$\overline{ror}$					
Mean	10%	12%	10%	12%	11%
Std. deviation	10%	11%	10%	11%	10%
Observations	80	65	78	67	145
$\overline{IAPR}$					
Mean	2.53	2.52	2.25	2.85	2.52
Std. deviation	2.91	2.88	2.71	3.08	2.89
Observations	73	61	73	61	134
$\overline{v_P}$					
Mean	1.27	1.04	1.16	1.18	1.17
Std. deviation	1.91	2.27	2.25	1.86	2.08
Observations	72	58	72	58	130

Figure B.1: Distribution of explicit and implicit measures of (dis)utility of personal information disclosure

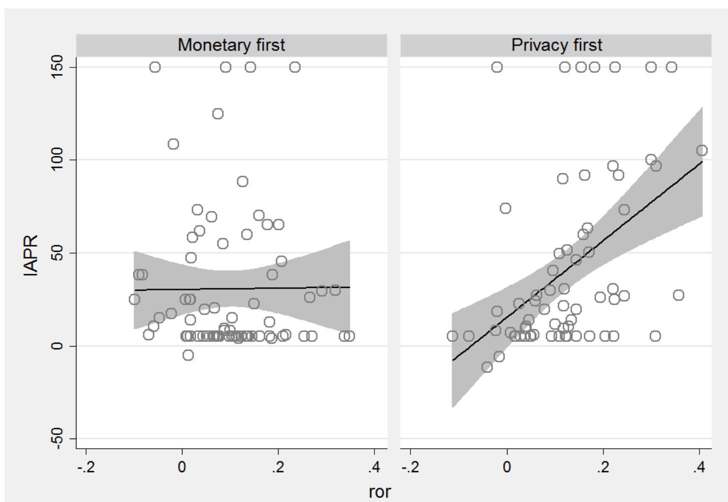


Note: Outliers (values that are 2 std. deviations away from the mean) are not shown.

Figure B.2: Scatterplot of $\overline{ror}$ and (dis)utility of privacy risk, $\overline{IAPR}$, by treatment and by order of elicitation, with prediction line of linear regression and 95% confidence interval for forecast.



(a) By treatment



(b) By order of elicitation

B.7 Regressions

Table B.11: Interval regression of $\overline{IAPR_i}$ over $\overline{ror_i}$.

Model	(1)	(2)	(3)	(4)	(5)
$\overline{ror_i}$	116.62**	113.62**	127.33***	122.54***	118.53***
	[42.63,190.62]	[39.21,188.02]	[54.70,199.96]	[50.27,194.81]	[48.13,188.93]
$\overline{ror_i} > 100$	109.76***	106.08***	67.47*	67.91*	75.08*
	[49.29,170.23]	[44.92,167.25]	[10.01,124.93]	[9.89,125.93]	[12.79,137.36]
Treatment with privacy shock		-4.47	-11.65	-12.44+	-12.88+
		[-19.81,10.86]	[-25.87,2.56]	[-26.88,2.00]	[-27.62,1.86]
Condition with privacy elicited first		8.11	3.19	5.50	-1.47
		[-7.36,23.58]	[-11.51,17.89]	[-9.22,20.23]	[-15.95,13.01]
Q3: Nr of participants known			-1.81	-1.03	0.20
			[-7.27,3.64]	[-6.77,4.71]	[-5.91,6.31]
Q5: Trust in experimenters			-6.63	-16.45	-1.78
			[-58.31,45.05]	[-68.94,36.03]	[-63.95,60.39]
WTA			0.53**	0.52**	0.59***
			[0.21,0.86]	[0.20,0.85]	[0.27,0.92]
WTP			1.72*	2.17*	2.38**
			[0.25,3.20]	[0.45,3.88]	[0.62,4.14]
Q16: General privacy concern			7.28+	5.42	6.12
			[-0.93,15.50]	[-3.06,13.90]	[-2.39,14.64]
Index of information revelation (Q17-Q20)			5.02	3.01	-2.53
			[-4.18,14.22]	[-6.28,12.29]	[-12.10,7.03]
Q21: Victim of invasion of privacy			17.40*	14.93+	22.06*
			[0.30,34.50]	[-2.85,32.70]	[4.02,40.11]
Q22: Westin's pragmatist			-4.01	-3.53	-1.33
			[-21.06,13.05]	[-20.92,13.85]	[-18.77,16.10]
Q22: Westin's fundamentalist			11.23	15.44	30.97**
			[-8.89,31.35]	[-5.92,36.80]	[9.06,52.89]
Index for privacy settings online (Q26-Q29)			-4.51	-3.30	1.36
			[-12.85,3.82]	[-11.89,5.28]	[-7.64,10.35]
Q30: Index of self-disclosure			1.23	1.01	0.81
			[-0.75,3.21]	[-1.00,3.02]	[-1.26,2.89]
Index of conformity in preliminary questionnaire			-1.69	-8.12	-21.86
			[-120.53,117.16]	[-128.38,112.14]	[-146.45,102.74]
Index of risk attitude (Q31-Q32)				-4.42+	-6.56*
				[-9.22,0.38]	[-11.63,-1.50]
Index of trust (Q33-Q37)				1.11	0.90
				[-3.24,5.46]	[-3.56,5.36]
Q23: Number of close friends				0.92	0.21
				[-0.59,2.43]	[-1.30,1.72]
Q25: Number of online connections				-0.00	-0.01
				[-0.02,0.01]	[-0.02,0.01]
Constant	23.88***	22.47**	8.88	7.83	-55.72
	[12.67,35.09]	[8.10,36.83]	[-75.89,93.64]	[-77.93,93.58]	[-157.99,46.54]
Socio-demographic controls	No	No	No	No	Yes
N	148	148	143	140	140
of which right-censored	14	14	13	13	13
log likelihood	-725.56	-724.83	-685.57	-668.16	-655.90
LR χ^2(degrees of freedom)	19*** (2)	21*** (4)	51*** (16)	55*** (20)	80*** (39)

95% confidence intervals in brackets
$+\ p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.12: Panel random-effects interval-data regression, number of safe choices in privacy lotteries by table.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Safe choices in monetary	0.632***	0.659***	0.617**	0.530**	0.489**	0.517**
lotteries	[0.29,0.98]	[0.30,1.02]	[0.24,0.99]	[0.17,0.89]	[0.13,0.85]	[0.18,0.86]
Table 6		-1.332***	-1.332***	-1.321***	-1.356***	-1.358***
		[-1.81,-0.86]	[-1.81,-0.86]	[-1.81,-0.83]	[-1.85,-0.86]	[-1.86,-0.86]
Table 7		-1.799***	-1.800***	-1.795***	-1.840***	-1.841***
		[-2.27,-1.33]	[-2.27,-1.33]	[-2.28,-1.31]	[-2.34,-1.35]	[-2.34,-1.35]
Table 8		9.500***	9.498***	9.498***	9.427***	9.426***
		[8.70,10.30]	[8.70,10.30]	[8.68,10.32]	[8.59,10.26]	[8.59,10.26]
Treatment with privacy shock			-0.226	-0.791	-0.843	-1.070+
			[-1.44,0.99]	[-1.90,0.32]	[-1.97,0.28]	[-2.20,0.06]
Condition with privacy elicited			0.701	0.255	0.449	-0.0883
first			[-0.53,1.94]	[-0.92,1.43]	[-0.73,1.62]	[-1.22,1.04]
Q3: Nr of participants known				-0.328	-0.327	-0.225
				[-0.75,0.09]	[-0.77,0.12]	[-0.69,0.24]
Q5: Trust in experimenters				-1.671	-2.012	-0.0322
				[-5.82,2.48]	[-6.21,2.19]	[-4.82,4.76]
WTA				0.0434***	0.0434***	0.0483***
				[0.02,0.07]	[0.02,0.07]	[0.02,0.07]
WTP				0.134*	0.168*	0.164*
				[0.02,0.25]	[0.03,0.30]	[0.03,0.30]
Q16: Generally privacy concern				0.721*	0.599+	0.781*
				[0.09,1.36]	[-0.06,1.25]	[0.13,1.43]
Index of information revelation				0.457	0.340	-0.125
(Q17-Q20)				[-0.26,1.17]	[-0.38,1.06]	[-0.85,0.60]
Q21: Victim of invasion of				1.241+	0.943	1.562*
privacy				[-0.08,2.56]	[-0.43,2.31]	[0.20,2.93]
Q22: Westin's pragmatist				-0.456	-0.398	-0.256
				[-1.78,0.87]	[-1.75,0.95]	[-1.58,1.07]
Q22: Westin's fundamentalist				0.973	1.168	2.308**
				[-0.58,2.52]	[-0.48,2.82]	[0.66,3.95]
Index for privacy settings online				-0.194	-0.162	0.269
(Q26-Q29)				[-0.84,0.46]	[-0.83,0.51]	[-0.42,0.95]
Q30: Index of self-disclosure				0.0313	0.00860	0.00305
				[-0.12,0.19]	[-0.15,0.17]	[-0.16,0.16]
Index of conformity in				-2.582	-3.117	-4.301
preliminary questionnaire				[-11.80,6.64]	[-12.44,6.20]	[-13.84,5.24]
Index of risk attitude (Q31-Q32)					-0.292	-0.472*
					[-0.67,0.08]	[-0.86,-0.08]
Index of trust (Q33-Q37)					0.163	0.124
					[-0.18,0.50]	[-0.22,0.46]
Q23: Number of close friends					0.0722	0.0259
					[-0.05,0.19]	[-0.09,0.14]
Q25: Number of online					0.0000371	-0.000180
connections					[-0.00,0.00]	[-0.00,0.00]
Constant	3.231**	1.672	1.737	2.705	2.956	-1.400
	[0.78,5.68]	[-0.92,4.27]	[-0.86,4.33]	[-4.69,10.10]	[-4.50,10.41]	[-9.81,7.01]
Socio-demographic controls	No	No	No	No	No	Yes
N observations	592	592	592	572	560	560
of which left-censored	5	5	5	5	5	5
of which right-censored	212	212	212	204	201	201
N individuals	148	148	148	143	140	140
log likelihood	-1386	-1030	-1030	-982	-959	-944
Wald χ^2 (degrees of freedom)	13*** (1)	810*** (4)	812*** (6)	803*** (18)	776*** (22)	802*** (41)

95% confidence intervals in brackets
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.8 Summary of answers to the post-experimental questionnaire

	Mean	SD	Min	Max
Part A: About the experiment				
Q2. Ease of understanding	2.14	0.61	0	3
(0 very difficult, 3 not difficult at all)				
Q3. Number of known other participants	1.28	1.31	0	5
Share which knew another participant (s)	66%			
Q4. Appropriate remuneration (0 No, 1 Yes)	70%			
Q5. Trust experimenters (0 No, 1 Yes)	97%			
Q6. WTA, Euro	36.2	142	0	1000
WTA excluding outliers, Euro	16.1	25.4	0	200
Q7. WTP, Euro	10	83.7	0	1000
WTP excluding outliers, Euro	1.92	4.85	0	30
Part B: Demographics				
Q8. Males	66%			
Q9. Age				
18-25 years	94%			
26-30 years	6%			
Q10. Field of study:				
Social sciences	82%			
Technical sciences	10%			
Humanities and Arts	5%			
Natural sciences	1%			
Other	1%			
Q11. Education level:				
Secondary education	82%			
Bachelor's degree	15%			
Master's degree	3%			
Q12. Italians	93%			
Q13. Parents completed secondary education:				
None of the parents	16%			
One of the parents	25%			
Both parents	59%			
Q14. Size of city (inhabitants):				
> 1 million	3%			
100 001 - 1 000 000	16%			
10 001 - 100 000	49%			
1 001 - 10 000	28%			
< 1 000	4%			
Q15. Expenses per month:				
< Euro 500	43%			
Euro 501-800	41%			
Euro 801-1200	11%			

continued on the next page

	Mean	SD	Min	Max
Euro 1201-2000	1%			
>Euro 2000	0%			
No answer	4%			
Part C: Privacy preferences, OSN activities and self-disclosure				
Q16. General privacy concern (0 not concerned at all, 3 very concerned)	1.12	0.90	0	3
Q17. Willingness to provide Personal Identifying Information ("PII") to websites (0 very willing, 4 not willing at all)	2.68	0.91	0	4
Q18. Provide PII to websites if compensated (0 No, 1 Yes)	57%			
Q19. Willingness to provide information about tastes, interests and preferences to websites (0 very willing, 4 not willing at all)	1.57	1.18	0	4
Q20. Provide information about tastes, interests and preferences if compensated (0 No, 1 Yes)	86%			
Q21. Victim of privacy invasion (0 No, 1 Yes)	34%			
Q22. Westin's Privacy Index				
Unconcerned	44%			
Pragmatist	28%			
Fundamentalist	28%			
Q23. Number of close friends offline	6.37	4.79	1	30
Q24. Primary online social network (POSN)				
Facebook	80%			
Google+	2%			
Twitter	1%			
Pinterest	1%			
LinkedIn	1%			
Instagram	10%			
Not a member	5%			
Q25. Number of connections in POSN	545	488	0	3200
Q26. Name in POSN (if use)				
Real name	94%			
Pseudonym, and nobody knows who I am in real life	2%			
Pseudonym, but everybody knows who I am in real life	4%			
Q27. Profile picture in POSN (if use)				
Real photo	74%			
Real photo with other people	19%			
Photo of other person	2%			
Image of non human being	4%			
No photo at all	1%			
Q28. Privacy settings in POSN (if use)				
Public	13%			
Private	57%			

continued on the next page

	Mean	SD	Min	Max
Mostly public	11%			
Mostly private	19%			
Q29. Changed privacy settings in POSN (if use)				
Never	15%			
Immediately after registration	34%			
Several times	48%			
After misuse	3%			
Other	1%			
Q30. Self-disclosure index	-1.86	3.61	-13	10
Part D: Attitudes to risk and trust				
Q31. General risk attitude (0 averse, 10 risk -seeking)	5.91	1.6	1	10
Q32. Risk attitude in: (0 averse, 10 risk-seeking)				
Driving	3.6	2.66	0	10
Finance	4.28	2.31	0	10
Sports	6.69	2.18	0	10
Career	4.63	2.34	0	10
Health	3.03	2.65	0	10
Trusting strangers	4.41	2.54	0	10
Q33. Trust people (0 agree, 3 disagree)	1.6	0.71	0	3
Q34. Cannot rely on people (idem)	1.82	0.72	0	3
Q35. Should not trust strangers (idem)	0.85	0.65	0	3
Q36. People try to be fair (0 No, 1 Yes)	33%			
Q37. People follow their own interests (idem)	83%			

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