Düsseldorf Institute
for Competition Economics

DISCUSSION PAPER

No 308

Online Privacy and Market Structure: Theory and Evidence

Lorien Sabatino,
Geza Sapi

February 2019

HEINRICH HEINE
UNIVERSITÄT DÜSSELDORF

d|u|p düsseldorf university press

IMPRINT

DICE DISCUSSION PAPER

Published by

düsseldorf university press (dup) on behalf of
Heinrich-Heine-Universität Düsseldorf, Faculty of Economics,
Düsseldorf Institute for Competition Economics (DICE), Universitätsstraße 1,
40225 Düsseldorf, Germany
www.dice.hhu.de

Editor:

Prof. Dr. Hans-Theo Normann
Düsseldorf Institute for Competition Economics (DICE)
Phone: +49(0) 211-81-15125, e-mail: normann@dice.hhu.de

DICE DISCUSSION PAPER

ISSN 2190-9938 (online) – ISBN 978-3-86304-307-0

Online Privacy and Market Structure: Theory and Evidence*

Lorien Sabatino† Geza Sapi‡

February 2019

*We would like to thank Szabolcs Lorincz, Mario Pagliero, and Carlo Cambini for helpful comments.

†Corresponding author. Department of Production and Management Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Torino, Italy. E-mail: lorien.sabatino@polito.it.

‡European Commission DG COMP - Chief Economist Team and Düsseldorf Institute for Competition Economics (DICE), Heinrich Heine University of Düsseldorf. E-mail: sapi@dice.uni-duesseldorf.de. The views expressed in this article are solely those of the authors and may not, under any circumstances, be regarded as representing an official position of the European Commission.

Abstract

This paper investigates how privacy regulation affects the structure of online markets. We provide a simple theoretical model capturing the basic trade-off between the degree of privacy intrusion and the informativeness of advertising. We derive empirically testable hypotheses regarding a possibly asymmetric effect of privacy regulation on large and small firms using a diff-diff-diff model with heterogeneous treatment timing. Our theoretical model predicts that privacy regulation may affect predominantly large firms, even if - as our data confirms - these large firms tend to offer more privacy. Our empirical results show that, if any, only large firms were negatively affected, suggesting that privacy regulation might boost competition by leveling out the playing field for small firms.

JEL-Classification: D43, L86, M37, M38

Keywords: Privacy, Competition, Regulation, ePrivacy Directive

1 Introduction

Firms in the digital economy collect customer data at an unprecedented rate. Electronic commerce in physical and digital goods is fueled by recommendation engines: algorithms that rely on user data on demographics, previous purchases and other preferences to predict products and services an online shopper may be interested in. Commentators often attribute a large share of the stellar success of internet giants like Amazon and Netflix to the ability of these firms to successfully recommend products to their users based on data and analytics (Arora 2016).

At the same time, consumers are increasingly mindful about online privacy. While in 2011 around 40% of surveyed Europeans were concerned about their behavior being recorded through the internet when browsing, downloading files, and accessing content online (Eurobarometer 2011, page 67), in 2015 less than a quarter of Europeans reported to trust online businesses to protect their personal data (Eurobarometer 2015, page 25). As a response to the increased privacy concerns of the public, the European Union (EU) put into force a series of privacy regulations since the early 2000s.[1] In 2018 the European Commission put forward a proposal for an EU-wide ePrivacy Regulation with the aim of replacing the current ePrivacy Directive of 2009 (European Commission 2018). The proposal received a lot of criticism from industry representatives, expressing concerns about the effect of stricter online privacy rules on the competitiveness or European businesses, adding that the regulation may benefit large firms.[2]

We do three things in this paper. First, we investigate empirically whether large firms or small firms offer more privacy, and argue that - in contrast to conventional wisdom - larger (more visited) websites seem to fare better on privacy ratings. Second, we propose a simple theoretical model of competition in the online retail sector that captures the main trade-off between the informativeness of advertising and the degree of privacy intrusion (Tucker 2012). Our model predicts that privacy regulation affects first and foremost the profits of larger firms, even if - as our data shows - these larger firms actually offer more privacy. Third, we empirically test the existing theories regarding the effect of privacy regulation on market structure in e-commerce. We do this by exploiting the previous 2009 revision of the ePrivacy Directive (2009/136/EC). In particular, we employ a *difference-in-difference-in-differences* (DDD) estimator to identify the effect of increased privacy regulation on European firms active in the online retail sector. We exploit time variation in the implementation of the ePrivacy Directive by EU Member States by constructing a DDD estimator with heterogeneous treatment timing. Our data allows comparing European e-commerce businesses to a control group consisting of firms primarily active in the United States as well as brick and mortar firms selling similar consumer discretionary products as their online counterparts.

Our empirical results indicate that the 2009 ePrivacy Directive had no significant effect on the revenues and profits of European e-commerce firms: if any, only large firms might have been negatively affected. This stands in strong contrast to other empirical studies on the effect of privacy regulation that tend to emphasize negative effects on the industry (Lambrecht 2017, Goldfarb and Tucker 2011, Jia, Jin and Wagman 2018). Moreover, we argue that standard *difference-in-differences* (DiD) approaches do not allow to identify the causal impact of the policy change in this particular context.

Overall, our results carry strong implications for the intersection of competition and data protection policy. They cast some doubt on the traditional antitrust view that regards market power as a precondition for firms having the ability and incentive to exploit their users for data. Our empirical results looking at the last round of revision of the very same regulation suggest that industry fears may be overexaggerated. Our theory predicts that if there is any effect of the regulation on online businesses, larger firms are more likely to carry the burden. Hence, privacy regulation may complement antitrust policy and help boost competition in online markets by creating an equal playing field for smaller firms that face technologically advanced rivals.

1.1 The ePrivacy Directive

Our research is motivated by the ongoing debate in Europe about the ePrivacy Regulation (Apostle 2018, Khan 2018, Singer 2018). The ePrivacy Regulation builds on the former ePrivacy Directive of 2002 and intends to regulate how online businesses handle data and use cookies. The adoption of the ePrivacy Regulation is staggering mainly due to concerns about its implications on the performance of European online businesses.

Our empirical assessment focuses on the predecessor of the proposed ePrivacy regulation, namely the 2009 revision of the ePrivacy Directive in the European Union (Directive 2009/136/EC), also known as the *Cookie Law*. The ePrivacy Directive was first enacted in the EU as the Privacy and Electronic Communications Directive (2002/58/EC) in 2002.

The 2002 ePrivacy Directive introduced stringent rules for online businesses to handle traffic data, ensure the confidentiality of user information, limit unsolicited messages and placing, storing and using cookies.[3] Importantly for our work, the ePrivacy Directive applies only to firms active in online business. We exploit this aspect in our empirical analysis in the choice of our control group, which will also consist of comparable offline retail businesses.

Following its 2002 enactment the ePrivacy Directive was amended in 2006 (Directive 2006/24/EC) and a major change followed in 2009 (Directive 2009/136/EC), which constitutes the subject of our empirical analysis. The main novelty introduced by the 2009 revision of the ePrivacy Directive is its Article 5(3), further regulating the acquisition, storage and use of cookies (Kosta 2013). In particular, the revision allowed the placement of cookies on a user's computer under two conditions. First, the user should be provided with clear and comprehensive information about the cookie and its use. The second condition is that the user must give his or her explicit consent before placing the cookie. In effect, this amounted to a transition to an opt-in privacy regime and moving away from the previous opt-out system. In online markets where defaults choices are hard to resist (Lohr 2011), the practical consequences of such a regime change may be very large.

Users browsing European websites will be familiar with a practical implication of the 2009 revision of the ePrivacy Directive: this regulation introduced the widespread use of pop-ups asking for consent to cookies that are in place ever since. However, this is not the only effect. It is widely perceived that the ePrivacy Directive made obtaining, storing and using cookies more difficult in Europe than in the United States (Lambrecht 2017, Goldfarb and Tucker 2011). Firms in electronic commerce and other online sectors voiced strong concerns about eroding profitability of online advertising as a result of the Directive (Goldfarb and Tucker 2011).

In this article we investigate how profits and revenues of electronic commerce businesses active in the European Union changed as a result of strengthening privacy regulations with the 2009 revision of the ePrivacy Directive. We are particularly interested in whether the regulation affected the structure of these markets by a potentially asymmetric effect on large and small businesses.

1.2 Literature Review

Our research is related to the rich and growing body of literature on the economics and marketing aspects of privacy, recently surveyed extensively by Acquisti, et al. (2016). A closely related theoretical research line in this strand investigates how the ability of firms to recognize customers and send targeted offers affects market outcomes in an oligopolistic setting. Shy and Stenbacka (2016) show that when a firm controls consumer privacy, it uses that information to optimally segment customers. Eventually, as in the seminal work of Thisse and Vives (1988), price discrimination can intensify competition and firms may prefer to avoid such outcome by strategically reducing the accuracy of targeted promotions, avoiding investment in customer addressability or seeking a commitment mechanisms not to price discriminate.

A recent article close to our theoretical approach is Kox et al. (2017), who analyze a model of websites acting as two-sided platforms matching advertisers to consumers. Websites can strategically choose the level of targeting of ads but consumers dislike being targeted. As Shy and Stenbacka (2016), these authors find that increased targeting boosts competition and the websites' ability to target advertisements results in a Prisoners' Dilemma-like outcome. A similar setup is employed by Baye and Sapi (2017), who develop a model of oligopolistic price discrimination applied to mobile geo-targeting. The authors show that the Prisoners' Dilemma often encountered in the literature on competitive price discrimination disappears when consumers have similar preferences and/or when the data are particularly precise.

Particularly close papers to ours are Campbell et al. (2015), Lambrecht (2017) , Goldfarb and Tucker (2011) and Jia, Jin and Wagman (2018). Similar to our paper, these articles revolve around the effects of the ePrivacy Directive. Campbell et al. (2015) develop a theoretical model of competition between a generalist and specialist content provider. The specialist firm offers better content in a niche domain. The generalist covers a broader range of topics but in less depth. User data allows both firms to increase the revenue per customer. The main idea is that the ePrivacy regulation may make it costlier for users to give consent to data processing, for example because it requires additional time to read and understand privacy policies before approving intrusive pop-ups asking for consent. The extra costs required to obtain consent will disproportionately affect the specialist firm, which in some cases may choose not to enter. This benefits the large generalist firm and is to the detriment of users. Our theoretical setup differs in two main aspects. First, we do not regard privacy regulation as a cost on users, but as a cap on privacy intrusiveness of websites. Second, in Campbell et al. (2015) the asymmetry between firms arises from the content they offer. In our theoretical setup asymmetry arises from firms' technology to turn data into revenue. This is a crucial difference that results in a contrasting theoretical prediction, whereby unlike in Campbell et al. (2015) large firms are expected to be affected harder by privacy regulation. This expectation is confirmed by our empirical results, showing that the ePrivacy Regulation reduced the revenues of large firms significantly but left small firms unaffected.

Lambrecht (2017) provides a recent empirical impact assessment of the 2002 enactment of the ePrivacy Directive and looks at whether and how the Directive affected venture capital investment into start ups active in online advertising, online news, and cloud computing. Using similar investments in the U.S. as benchmark and controlling for drivers of venture capital investment, the author finds that the passage of the 2002 ePrivacy Directive significantly dampened EU venture capital investments in the analyzed sectors. As Lambrecht (2017), our empirical assessment takes U.S. firms as control group. However, instead of investment we focus on profits and revenues in online retail, a sector not studied by Lambrecht (2017). The results of Lambrecht (2017) are consistent with the view that privacy regulation affects predominantly small firms negatively: reduced expected revenues may be the reason why venture capital investment into online startups have been found to decrease. We find the opposite, whereby small firms are left unaffected and large firms are hit hard. This difference in result suggests that there may be sectorial heterogeneities in the impact of privacy regulation. A further difference of our empirical analysis to Lambrecht (2017) is in our identification strategy: while Lambrecht (2017) employs a DiD approach comparing the EU and the U.S. before and after the regulation, we adopt a DDD estimator distinguishing in addition between comparable online and offline firms.

Goldfarb and Tucker (2011) use data on 3.3 million survey-takers randomly exposed to 9,596 online display (banner) advertising campaigns to investigate the effect of the 2002 Privacy Directive (2002/58/EC) on the effectiveness of advertising campaigns. The authors exploit differences in the national transposition of the Privacy Directive in Europe to identify the effect of the regulation on the respondents' stated purchase intent after having seen an ad. Goldfarb and Tucker (2011) find that the 2002 Privacy Directive significantly reduced the effectiveness of online banner ads by reducing the ability of advertisers to track users and offer targeted advertisements. Our theoretical model incorporates the effect empirically identified by Goldfarb and Tucker (2011), and explicitly takes into account that data may allow firms to increase revenues by targeting offers at users. As opposed to individual ad campaigns, the focus of our theoretical and empirical analysis is the level of the market, where we investigate whether privacy regulation affects large and small firms differently.

Jia, Jin and Wagman (2018) provide an early assessment of the European General Data Protection Regulation (GDPR) that came into effect in May 2018. The authors look at the effect of the GDPR on venture capital investment activity, using similar investments in the U.S. as control group and argue that the regulation reduced EU ventures, relative to their U.S. counterparts. These negative effects are significant in the overall dollar amounts raised across funding deals, the number of deals, and the dollar amount raised per individual deal.

Our results point against the empirical results of Goldfarb and Tucker (2011), Lambrecht (2017) and Jia, Jin and Wagman (2018). While these papers attribute a negative effect to privacy regulation on businesses, we find no significant negative effect on revenues and profits. In terms of theory, while Campbell and et al. (2015) highlight that privacy regulation is likely to hit smaller firms the hardest, we see no such effect empirically, and argue based on a novel theory that if any effect on firms should arise, it may be large firms carrying the heaviest burden.

2 A Theoretical Model of Privacy in E-Commerce

Our theoretical framework is motivated by e-commerce environments in which firms of the treatment group of our empirical analysis operate. We have in mind firms like Expedia, Groupon, and Otto.de. These firms are typically retail platforms operating e-commerce websites selling a vast array of third-party products offered by various brands.

In particular, we focus on a market consisting of two competing multiproduct online retailers $i \in \{A, B\}$. The retailers sell the products of several brands on their websites and finance themselves from slotting fees these brands pay in exchange for listing their products. Retailers provide services at zero marginal cost and realize profits

$$\Pi_i = a_i p_i, \tag{1}$$

where a_i is the number of brands choosing to be listed at the retailer and p_i is the uniform slotting fee of Retailer i.

Consumers regard the retailers as differentiated. Retailers can be thought of as being located at the endpoints of a line of unit length along which consumers are uniformly distributed with unit mass. For convenience we assume that Retailer 1 is located at endpoint 0 and Retailer 2 at endpoint 1 of the unit line. Consumers are characterized by an address on the line so that their distance to the endpoints represent their preference for each retailer. When purchasing from a retailer, the consumer incurs a disutility that increases linearly in proportion to the distance to the retailer. Retailers 1 and 2 are free to use for consumers but they collect data on their users. These data in turn enable brands to better target products to users. In particular, retailers chose their privacy policy $q_i \geq 0$, where a larger value represents more intense use of data and consequently less user privacy. Consumers value privacy and are informed about the retailers' use of data and choice of q_i. When choosing between the retailers, consumers single home. A consumer at location x faces the choice between realizing the following utilities at Retailers 1 or 2:

$$U_1 = V - tx - q_1$$

$$U_2 = V - t(1-x) - q_2,$$

where V is a basic utility from visiting a retailer and t is a transportation cost parameter per unit distance in the preference space. We assume that V is high enough so that in equilibrium every consumer visits one of the retailers.

The retailers operate websites that provide information about products of different brands. For the brands the retailer's website is a marketing channel to consumers, allowing them to target products at individual users based on the data the retailer's website collects. Brands decide on whether to advertise at Retailers 1 and 2 and face no capacity constraint. In particular, they may decide to list their products on either retailer's website, on both websites or refrain from listing at the retailers. If brand j lists its product on Retailer i's website, the brand incurs two types of cost. First, the slotting allowance p_i that is uniform to all brands at Retailer i. Second, a retailer-specific cost c_{ij}. The latter captures the brand's fixed cost associated with listing its product on Retailer i's website other than the slotting fee, such as costs to comply with the technical requirements of the retailer and designing a digital advertisement. We assume that c_{1j} and c_{2j} are uniformly distributed on the interval $c_{ij} \in [0, \infty)$. This means that brand j expects the following profit from offering its product priced at $\overline{p}$ on the website of Retailer i:

$$\pi_{ji} = \Pr\{Sale_i\} n_i \overline{p_j} - p_i - c_{ij},$$

where n_i and $\overline{p_j}$ respectively denote Retailer i's share among users and the average price of Brand j's product. $\Pr\{Sale_i\}$ is the probability of successfully selling the product to a consumer through Retailer i. In particular, we assume that this probability depends on q_i, the privacy policy of that retailer, so that $\Pr\{Sale_i\} = s_i(q_i)$, with $\partial s_i(q_i)/\partial q_i > 0$ and $\partial^2 s_i(q_i)/\partial q_i^2 < 0$. The more data the retailer collects through its website, the higher the probability that the brand realizes a sale via the retailer.

Given that brands face no capacity constraint, they will decide to be listed at each retailer as long as doing so entails positive expected profits, which is the case when $\Pr\{Sale_i\} n_i \overline{p_j} - p_i \geq c_{ij}$. There will be a marginal brand at each retailer with fixed cost $\overline{c_i}$ for which this relationship holds with equality so that the brand is indifferent between being present at the retailer or not. The number of brands listed on the platform equals the fixed costs of the marginal brand, with $a_i = \overline{c_i}$. The demand function of brands for retail space is therefore given by

$$a_i = \Pr\{Sale_i\} n_i \overline{p_j} - p_i. \tag{2}$$

To economize on parameters we without loss of generality normalize $\overline{p_j}$ to 1. To obtain closed form solutions we assume an explicit functional form for the probability of successful sale. In particular, let

$$\Pr\{Sale_i\} = s_i(q_i) = 1 - e^{-\Delta_i q_i}, \tag{3}$$

with $\Delta_2 = 1$ and $\Delta_1 = \Delta > 1$. Parameter Δ represents Retailer 1's *technology advantage* in enabling brands to convert user data into sales.[4] In the following we will sometimes refer to Retailer 1 as the firm with *superior data technology*.

This theoretical setup is simple and tractable, and captures the main trade-off in electronic commerce regarding privacy: retailers value data because it increases revenues. Users however value privacy and prefer to reveal less data. To focus on the essentials, we consciously abstract away from possible feedback loop effects arising from consumers anticipating how revealing their data may affect prices and offers at the retailers, and form no expectations about the prices they expect to see at the websites. Although this admittedly corresponds to some assumed level of consumer myopia, we consider this both practical and realistic in e-commerce.[5]

The sequence of decisions is as follows. Retailers simultaneously and independently decide on the privacy-intrusiveness of their websites, q_i. They subsequently simultaneously and independently decide on the uniform slotting fee p_i. Brands chose whether to list their product at a retailer's website and consumers chose which retailer's website to visit.

2.1 Equilibrium Analysis

Consumers single home when they decide which retailer's website to visit and surf to the website of the retailer offering higher utility. We can find the address $\overline{x}$ of the marginal consumer that is indifferent between the retailers. Under our assumptions this address directly determines the market share of the retailers among users, so that $\overline{x} = n_1$ and $1 - \overline{x} = n_2$. The demand for each retailer is

$$n_1 = (q_2 - q_1 + t)/2t, \tag{4}$$
$$n_2 = (q_1 - q_2 + t)/2t.$$

We can plug these values together with Expressions (2) and (3) into Expression (1) to obtain the profit retailers seek to maximize by setting slotting fees:

$$\Pi_1 = p_1 \left[(1 - e^{-\Delta q_1}) \frac{q_2 - q_1 + t}{2t} - p_1 \right], \tag{5}$$
$$\Pi_2 = p_2 \left[(1 - e^{-q_2}) \left(1 - \frac{q_1 - q_2 + t}{2t} \right) - p_2 \right].$$

Maximizing with respect to the slotting fees yields

$$p_1^*(q_1, q_2) = \frac{\left(1 - e^{-\Delta q_1}\right)(q_2 - q_1 + t)}{4t}, \tag{6}$$
$$p_2^*(q_2, q_1) = \frac{(1 - e^{-q_2})(q_1 - q_2 + t)}{4t}.$$

Plugging these back into Expression (5) results in the following reaction functions:

$$q_1(q_2) = q_2 + t + \frac{1 - W\left(e^{\Delta(q_2+t)+1}\right)}{\Delta}, \tag{7}$$
$$q_2(q_1) = q_1 + t + 1 - \frac{W\left(e^{q_1+t+1}\right)}{\Delta},$$

where $W(.)$ is the *Lambert W* function that satisfies $W(ze^z) = f^{-1}(ze^z) = z$, see Corless et al. (1996). Notably, this function is positive and concave over the domain of real numbers. Using this property we can take the partial derivatives of the reaction functions with respect to the rival retailer's privacy intrusiveness to establish that reaction functions are upward sloping and hence privacy decisions are strategic complements:

$$\frac{\partial q_1(q_2)}{\partial q_2} = \left[W\left(e^{\Delta(q_2+t)+1}\right)\right]^{-1} > 0,$$
$$\frac{\partial q_2(q_1)}{\partial q_1} = \left[W\left(e^{q_1+t+1}\right)\right]^{-1} > 0.$$

Having set up the basic model, the following proposition describes the equilibrium absent privacy regulation.

Proposition 1: *In equilibrium the retailer with superior data technology (Retailer 1) has higher market share among consumers ($n_1^* > n_2^*$), adopts a less intrusive privacy policy ($q_1^* < q_2^*$), offers brands higher probability of sale ($s_1^* > s_2^*$), has higher slotting fees ($p_1^* > p_2^*$), offers more products ($a_1^* > a_2^*$) and realizes higher profits ($\Pi_1^* > \Pi_2^*$) than the rival.*

Proof: See Appendix.

The main result is that the firm with superior data technology is larger than the rival, yet it offers a higher level of privacy. This is an important insight that goes against the prevailing intuition in competition policy, where market power is traditionally regarded as a precondition for the ability and incentive of firms to exploit users for their data. In our case the contrary holds: higher level of privacy is the precise reason why Retailer 1 is larger than the rival. Since it needs to obtain less data on consumers due to its superior technology to turn those data into increased sales, Retailer 1 can outcompete Retailer 2 in privacy policy and provide services in a less intrusive manner. The crucial assumption is that Retailer 1 is superior in *data technology.* If instead of modeling asymmetry on the advertiser side we had assumed that a retailer was simply more appealing to users, e.g. the basic utility consumers realize at the firm was $V_1 > V_2$ instead of equal V, a markedly different relationship between technology advantage, market power and privacy intrusiveness would emerge. In that case the more appealing retailer would be larger and that firm would also have a more intrusive privacy policy as it was able to use its appeal to consumers to exploit them by requiring more data.

Some empirical facts seem to validate the prediction of our model that larger firms offer more privacy on their websites than smaller ones. We gathered traffic data for the 6,000 most popular websites in the U.S. in terms of monthly visitors from QuantCast.org. We furthermore obtained a privacy score for these websites from PrivacyScore.org. This organization rates websites according to four privacy dimensions: whether tracking services are used, whether selected attacks are prevented, the quality of encryption during data transmission to the website and the quality when sending e-mails to an existing e-mail

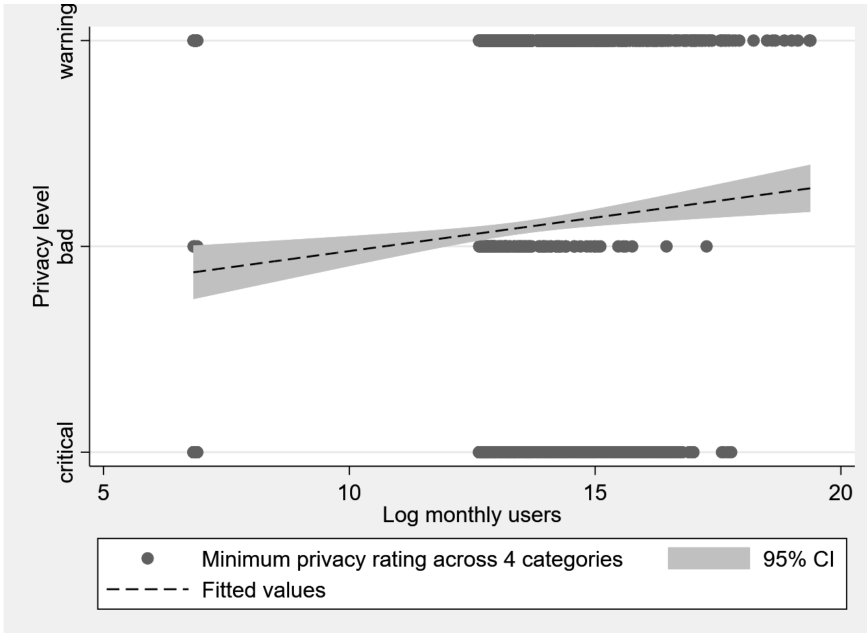


Figure 1: Relationship between website popularity and privacy level.

server. The precise methodology is outlined in more detail in Maass (2017). We could match the privacy score data with monthly traffic for 3,952 websites. Privacy ratings are ordinally measured on a five level scale. We associated numerical values with these categories as follows: critical (-3), bad (-2), warning (-1), neutral (0), good (1). Figure (1) depicts the relationship between the (log number of) monthly users and the lowest privacy rating of the website across the four evaluated categories. Based on this simple analysis it appears that larger websites offer more privacy than less frequented ones.[6]

2.2 Regulating E-Privacy

A regulation of e-privacy has the aim of increasing the privacy level of online services. We can think of it analytically as a cap on q_i. How does such regulation affect competition between large and small firms? We extend our theoretical model to address this question.

To do so, we use the model above to numerically calculate the equilibrium without regulation. For simplicity we then assume that the regulation imposes a cap on privacy which equals the privacy level offered by the less intrusive firm (Retailer 1) in the absence of privacy regulation. We then assess how key model variables change when the regulation is introduced. The main variable of interest for the following empirical analysis is the percentage change in profits at each firm. The results of the numerical simulation are in Table 1. The following proposition sums up the insights of this numerical simulation.

Proposition 2: *Regulation that caps privacy intrusiveness at the pre-regulation level ($\overline{q}$ of the less intrusive firm has the following effect on the equilibrium: The regulation is not binding for the retailer with superior data technology (Retailer 1 and only binds for the rival ($q_2^* = \overline{q}$. The retailer with superior data technology (Retailer 1 loses market share to the rival (n_1^* decreases), its profits are decreased in percentage terms more than those of the rival ($|\Pi_1\%| > |\Pi_2\%|$, the probability of sale, slotting fees and number of products sold decrease at both retailers.*

Table 1: Results from Numerical Simulation

t	1	1	2	2
Δ	2	3	2	3
$n_1(change)$	-0.029	-0.053	-0.04	-0.07
Π_1(%change)	-14	-22	-17	-24
Π_2(%change)	-6	-11	-7	-16
q_1(before)	0.575	0.493	0.842	0.689
q_2(before)	0.653	0.625	1.03	0.992
q_1(after)	0.556	0.468	0.811	0.654
q_2(after)	0.575	0.493	0.842	0.689
p_1(change)	-0.013	-0.025	-0.019	-0.033
p_2(change)	-0.003	-0.006	-0.006	-0.011

We assumed for the numerical simulations that the regulation caps the privacy intrusiveness of Retailer 2 at the pre-regulation level of the retailer with superior data technology (Retailer 1). Since privacy choices are strategic complements, the reduction of the privacy intrusiveness of Retailer 2 by the regulation also induces Retailer 1 to offer more privacy to consumers. This also means that such a regulation is not binding for Retailer 1 and only binds for Retailer 2.

Before venturing on the empirical analysis, we summarize the main insights emerging from this simple theoretical setup. The main result of the proposed model is that, perhaps somewhat surprisingly, the profits of the larger Retailer 1 are hit harder by the regulation than those of the smaller rival (Retailer 2), even if the former offers more privacy. The retailer with superior data technology experiences a higher percentage reduction in profits than the rival. The reasons is that the binding privacy regulation at Retailer 2 makes the latter attractive for consumers who value privacy. Retailer 2 therefore gains market share from Retailer 1. Privacy decisions being strategic complements results in both firms offering more privacy following the regulation, even if the regulation is binding for one firm only. However, since Retailer 1 is more productive in converting consumers into sales due to its superior data technology, losing these consumers imply a relatively high profit reduction for Retailer 1 that exceed the profit gains of Retailer 2 even in percentage terms. Our model is based on the idea that larger firms are better able to turn data into increased sales. This may be so due to technological reasons, such as economies of scale in data, or better analytical capabilities. If larger firms are more productive in data use, stripping them from their ability to gather customer data affects their revenues stronger (negatively) than those of smaller rivals. Our model also predicts that smaller firms are on average more privacy intrusive, a conjecture for which we are able to provide stylized evidence. Even if - as *sceptics* argue - the regulation is not directly binding for large firms, competition forces these businesses to reduce their privacy intrusiveness in response to their smaller rivals doing so.

3 Empirical Analysis

The next subsection discusses our empirical strategy to identify the causal effect of the introduction of the 2009 ePrivacy Directive on revenue and EBITDA in the retail sector. We exploit variation in the timing of implementation of the ePrivacy Directive, we construct a DDD estimator with heterogeneous treatment timing, and we argue that simple DiD does not identify the casual effect of the policy change. We then describe the data and provide summary statistics. Finally, estimation results are presented.

3.1 Empirical Strategy

We assess the impact of the ePrivacy Directive 2009/136/EC within the *difference-in-differences* (DiD) framework[7]. Our aim is to estimate the causal effect of the ePrivacy Directive on revenues and profits of firms operating in the retail sector. The introduction of the ePrivacy Directive is regarded as an exogenous shock affecting the online retail businesses, as it influences the capability of online firms to acquire data on potential customers. This is expected to affect their capability to match consumer preferences by provided targeted content.

Our empirical analysis relies on the ability to find a suitable control group, namely a subset of firms that have not been affected by the ePrivacy Directive. As the ePrivacy Directive applies only to businesses operating in the Internet, a possible approach could be comparing online retail firms with a control group of comparable brick-and-mortar retail firms in the European Union (EU), before and after the policy change. There are however two shortcomings of this strategy. Firstly, brick-and-mortar retailers may realize some sales via their Internet website and may therefore not be fully unaffected by the regulation. Secondly, online shopping taking off in recent years might increase both profits and revenues of online retailers relative to offline stores independently of the policy change. Another possibility is to focus on online retailers only, and use as control group firms operating in a geographical market not affected by the ePrivacy Directive, such as the United States. Here the main shortcoming is that the evolution of revenues and profits of retail firms might be systematically different in the U.S. and the EU for reasons other than the policy change.

Therefore we resort to a *difference-in-difference-in-differences* (DDD) estimation. In this setting, we use retail firms -online and offline - operating in the U.S., along with EU offline retail firms as controls. Online firms operating in the EU remain in the treatment group. This approach allows controlling for two main confounding factors: changes in revenues and profits due to idiosyncratic differences between the U.S. and the EU, and other factors affecting online firms than the policy change. We exploit variations in the timing of implementation of the ePrivacy Directive by the Member States. Heterogeneity in the treatment timing allows us to identify precisely the average effect of the introduction of the directive on our dependent variable. In such a setting, the control group includes not only U.S. firms, but also firms operating in Member States that have not implemented the Directive yet. That is, online European firms that experienced the policy change later act as controls too.[8]

Let $y_{i,t}$ be the logarithm of either profit (EBITDA) or revenue for firm i at time t. Our basic empirical specification is of the form:

$$y_{i,g,t} = \beta_0 + \beta_1 Post_{i,t} \times EU_i \times Online_i +$$

$$+ \sum_t \beta_{2,t} Time_t \times EU_i + \sum_t \beta_{3,t} Time_t \times Online_i + FE_i + FE_t + \epsilon_{i,t} \tag{8}$$

where EU_i is a dummy taking value one if firm i operates in the EU, while $Online_i$ is an indicator taking value 1 if firm i operates online; FE_i and FE_t are firm-specific and time fixed effects. The variables $Time_t \times EU_i$ and $Time_t \times Online_i$ are derived by the interaction of time-specific dummies with EU_i and $Online_i$ respectively. The coefficients $\beta_{2,t}$ capture the percentage difference of the dependent variable between firms operating in the EU and U.S. firms at time t; while $\beta_{3,t}$ capture the percentage difference of the dependent variable for online firms versus offline firms at time t. The variable $Post_{i,t}$ is a dummy that identifies the period covered by the policy change for firm i, depending on whether the Member State where i operates has implemented the ePrivacy Directive.[9]

The coefficient of interest in (8) is β_1, which captures the average causal effect of the policy change on the dependent variable. In particular, it captures the average effect of the introduction of the ePrivacy Directive on online firms in the EU. Since $Post_{i,t}$ varies across firms, depending on whether the country where i operates implemented the Directive, then EU online firms act as controls together with U.S. firms when the policy change has not taken place yet.[10]

We test the robustness of the results from the model (8) by estimating a dynamic model where we interact our covariate of interest $Treat \times Online$ with $Time_t$ year-specific dummies:

$$y_{i,t} = \beta_0 + \sum_t \beta_{1,t} Time_t \times EU_i \times Online_i + \sum_t \beta_{2,t} Time_t \times EU_i + \sum_t \beta_{3,t} Time_t \times Online_i +$$

$$+ \sum_t \beta_{4,t} Time_t + [\sum_g \beta_{5,g} Geo_g \times Trend_t + \sum_g \beta_{6,g} Geo_g \times Trend_t^2] + FE_i + \epsilon_{i,t} \quad (9)$$

where $y_{i,t}$ denotes the logarithm of either profit (EBITDA) or revenue for firm $i \in g$ at time t, g indexes the geographical market, i.e. the country where i operates.[11] The terms in square brackets include geographic-specific time trends, while FE_i denotes firm-specific fixed effects.[12] Here the parameters of interest are collected by the vector β_1, capturing the dynamic average causal effect of the policy change on the dependent variable.

3.2 Data

Our dataset consists of an unbalanced panel of firms active in online and offline retail sector either in the U.S. or in the EU for the period 2004-2016 from the S&P CapitalIQ database. For each firm we observe EBITDA, revenues, age and operating status. Along with SIC codes by primary activity the data provider offers its own classification of business domains. We focus exclusively on firms selling consumer discretionary products such as for example books, electronics and furniture. The sectors covered by the data are displayed in Table 2. This classification allows us to distinguish between firms selling similar products but differing in their respective reliance on online and brick-and-mortar distribution channels. We will refer to firms classified by our data provider as active in "*Internet and Direct Marketing Retail*" as "*online*", while firms operating in the other sectors will be defined as "*offline*".

Since the ePrivacy Directive applies only in the European Union, multinational firms active both in the EU as well as the United States pose a challenge in our data. As they typically report global financial figures, it is difficult to classify them to treatment (EU) or control (U.S.) regions. For these reasons we restrict our dataset to the subset of firms that report financials separately by geographic segment and realize at least 80% of their revenues in one particular national geographical market, either in the EU or the U.S. Our final dataset includes 145 firms active in the retail sector, with annual EBITDA and Revenues resulting in 1885 observations. Summary statistics are displayed in Table 3.

Our empirical strategy relies on the existence of firms that operate either online or offline, either in the U.S. or in the EU. Table 4 shows the distribution of firms in our sample across the four main categories necessary to implement the DDD analysis. We consider this distribution balanced across EU and U.S. as well as online and offline retail. Figures 4(a) and 4(b) display the trends of revenue and EBITDA respectively over these categories. The positive trend of the online retail sector compared to the offline both in Europe as well as in the U.S. confirms that a simple DiD strategy relying on European firms only would indeed likely yield biased estimates.[13] The DDD estimator is less prone to the same bias.

In order to identify the *Post* dummy in equation (8) we investigate when the ePrivacy Directive has been effectively implemented by the EU Member States. Table 5 shows when the ePrivacy Directive has been implemented by the Member States where the firms in our dataset operates.[14] Interestingly enough, the Directive was implemented between 2011 and

2013. Finland, United Kingdom, Sweden and France were the first converting the Directive into National law, while Poland and Slovenia the last ones.

3.3 Results

Tables 6 and 7 report results from ordinary least squares (OLS) estimation of the econometric model (8), showing the impact of the ePrivacy Directive on revenues and EBITDA respectively. In particular, column 1 displays results from the estimation over the whole dataset, while columns 2 and 3 show the results when we run the econometric model only on large and small firms respectively.[15]

The interactions $EU \times Time$ identifies the percentage difference of the dependent variable between EU firms and U.S. firms. In all specification the coefficients are negative and statistically significant, with increasing magnitude in later years, capturing the greater expansion of U.S. retail firms compared to European ones. Not controlling for this trend implies a negative bias on the coefficient of interest. Similarly, the interactions $Online \times Time$ describe the percentage difference of the dependent variable between online and offline firms. As expected, the coefficients are positive, statistically significant, and increasing in magnitude in later years. They capture the expansion trend of the online retail sector over the standard brick-and-mortar retail firms.

The coefficient of interest $Post \times EU \times Online$ captures the average causal effect of the introduction of the ePrivacy Directive on the dependent variable in percentage terms. We do not find any significant effect on both revenue and EBITDA when we run the model over the full sample of firms in our dataset (column 1). When we focus on large firms (column 2) we find a negative impact of the introduction of the ePrivacy Directive on both revenues and profits, although only the in the former the coefficient is statistically significant. The coefficient suggests the introduction of the ePrivacy Directive caused a reduction of in the revenues of large firms of around 22%. When we focus on small firms (column 3) we find a positive effect, although not significant.

Tables 8 and 9 display the results from the dynamic DDD model of equation (9) over the whole sample (columns 1 and 2), on large firms only (columns 3 and 4), and on small firms only (columns 5 and 6). The coefficients of interest are the interaction of $EU \times Online$ with yearly time dummies, and these coefficients should be interpreted as a percentage variation of the dependent variable for the treated - either revenue or EBITDA - over the base year 2004. We also include in the estimation of the dynamic model country-specific trends (both linear and quadratic), which capture macroeconomic trends that are common to firms operating in the same geographical market. For a better understanding of these results, we plot the point estimates and their 95 percent confidence intervals in Figures 5 and 6 for revenue and EBITDA respectively. Consistently with previous results, we find no significant effect of the introduction of the ePrivacy Directive on both revenues and profits in the whole sample, as the coefficients are never statistically different than zero after 2012. Although the same applies for small firms, we observe a negative trend for large firms on both revenues and profits. In fact the coefficients in columns 3 of Tables 8 and 9 become negative and statistically significant from 2012, explaining why we found a negative impact in the standard DDD.[16] However, when we include country-specific trends (column 4) the negative trend becomes flatter, and the coefficients are statistically different than zero from 2014 onward. Such negative trend is consistent with the fact that Member States implemented the Directive little by little. This is more evident by observing that in the mid panel of Figure 5 the coefficients of interest increase in absolute value right after 2012. That is, the dynamics changes when all EU firms are treated.

In summary, we find that the later implementation of the 2009 revised ePrivacy Directive had on average little impact on revenues and profits in the retail sector. We observe a negative effect for large firms, although only on revenues it is statistically significant. Estimates for small firms are of the opposite sign, but never significant.

4 Concluding Remarks

In this paper we investigate the relationship between privacy regulation and market structure. Our main aim is to provide policy guidance in the discussion surrounding the European Commission's proposed ePrivacy Regulation.

Our empirical assessment focuses on the revision of the 2009 ePrivacy Directive (*Cookie Law*) that introduced an opt-in system for cookies in the European Union. We find that the privacy regulation had little effect on the revenues and profits of e-commerce firms in Europe. Our empirical analysis builds from a *difference-in-difference-in-differences* estimation with heterogeneous treatment timing. We show that simple comparisons of Online versus Offline, or EU versus U.S. are misleading, since they do not control for confounding factors affecting firms belonging to the same group. Our results show that only large firms might be negatively affected, and that perhaps small firms might take advantage from stricter eprivacy regulations. This goes against the arguments of industry representatives who have harshly criticized privacy regulation as being harmful for businesses.

Based on a novel theory, we argue that if the newly proposed EU ePrivacy Regulation should have any effect on businesses, it can be expected to affect larger firms more negatively, even if these may offer more privacy than smaller ones. Our theoretical model is based on the idea that larger firms are better able to turn data into increased sales, for example due to technological reasons, such as economies of scale in data, or better analytical capabilities. If larger firms are more productive in data use, the regulation affects them disproportionately by reducing the amount of data available to these firms, as users are less likely to consent the cookie use. Our model also predicts that smaller firms are on average more privacy intrusive, a conjecture for which we are able to provide stylized evidence obtained from privacy ratings for thousands of websites in the use and traffic data. Even if - as *skeptics* argue - the privacy regulation may not directly binding for large firms, competition forces these businesses to reduce their privacy intrusiveness in response to their smaller rivals doing so, for whom the regulation may be binding.

Our results carry relevance for the ongoing debate about the proposed European ePrivacy Regulation, whose adoption is staggering predominantly due to concerns about the competitiveness of European online businesses. Our empirical results looking at the last round of revision of the very same regulation suggest industry fears may be overexaggerated. Our theory predicts that if there is any effect of the regulation on online businesses, larger firms are more likely to carry the burden.

5 References

1. Acquisti, Alessandro, Curtis Taylor, and Liad Wagman. "The economics of privacy." Journal of Economic Literature 54.2 (2016): 442-92.

2. Apostle, Julia. "We survived GDPR, now another EU privacy law looms." Financial Times, June 13, 2018.

3. Arora, A. "Recommendation engines: How Amazon and Netflix are winning the personalization battle." MarTech Advisor (2016).

4. Ashenfelter, Orley C., and David Card. "Using the longitudinal structure of earnings to estimate the effect of training programs." (1984).

5. Baye, Irina, and Geza Sapi. "Should Mobile Marketers Collect Other Data Than Geo-Location?." The Scandinavian Journal of Economics.

6. Campbell, James, Avi Goldfarb, and Catherine Tucker. "Privacy regulation and market structure." Journal of Economics & Management Strategy 24.1 (2015): 47-73.

7. Card, David. "Using regional variation in wages to measure the effects of the federal minimum wage." ILR Review 46.1 (1992): 22-37.

8. Card, David, and Alan B. Krueger. Minimum wages and employment: A case study of the fast food industry in New Jersey and Pennsylvania. No. w4509. National Bureau of Economic Research, 1993.

9. Corless, Robert M., et al. "On the LambertW function." Advances in Computational mathematics 5.1 (1996): 329-359.

10. Episerver (2018): Reimagining Commerce, https://www.episerver.com/globalassets/assets-website-structure/resources/guides-and-reports/episerver-reimagining-commerce-report-2018.pdf

11. Eurobarometer 2011: http://ec.europa.eu/commfrontoffice/publicopinion/archives/ebs/ebs_359_en.pdf.

12. Eurobarometer 2015: http://ec.europa.eu/commfrontoffice/publicopinion/archives/ebs/ebs_431_sum_en.pdf.

13. European Commission (2018): Proposal for an ePrivacy Regulation, Digital Single Market. https://ec.europa.eu/digital-single-market/en/proposal-eprivacy-regulation.

14. Goldfarb, Avi, and Catherine E. Tucker. "Privacy regulation and online advertising." Management science 57.1 (2011): 57-71.

15. Goodman-Bacon, Andrew. Difference-in-differences with variation in treatment timing. No. w25018. National Bureau of Economic Research, 2018.

16. Jia, Jian, Ginger Zhe Jin, and Liad Wagman. The Short-Run Effects of GDPR on Technology Venture Investment. No. w25248. National Bureau of Economic Research, 2018.

17. Khan, Mehreen. "EU states urged to agree online privacy 'cookie law'." Financial Times, April 24, 2018.

18. Kosta, Eleni. "Peeking into the cookie jar: the European approach towards the regulation of cookies." International journal of law and information technology 21.4 (2013): 380-406.

19. Kox, Henk, Bas Straathof, and Gijsbert Zwart. "Targeted advertising, platform competition, and privacy." Journal of Economics & Management Strategy 26.3 (2017): 557-570.

20. Lambrecht, Anja. "E-Privacy Provisions and Venture Capital Investments in the EU." (2017).

21. Lohr, Steve. "The default choice, so hard to resist." New York Times (2011).

22. Maass, Max, et al. "PrivacyScore: Improving Privacy and Security via Crowd-Sourced Benchmarks of Websites." Annual Privacy Forum. Springer, Cham, 2017.

23. Reinganum, Jennifer F. "Uncertain innovation and the persistence of monopoly." The American Economic Review 73.4 (1983): 741-748.

24. Shy, Oz, and Rune Stenbacka. "Customer privacy and competition." Journal of Economics & Management Strategy 25.3 (2016): 539-562.

25. Singer, Natasha. "The Next Privacy Battle in Europe Is Over This New Law." The New York Times, May 27, 2018.

26. Thisse, Jacques-Francois, and Xavier Vives. "On the strategic choice of spatial price policy." The American Economic Review (1988): 122-137.

27. Tucker, Catherine E. "The economics of advertising and privacy." International Journal of Industrial Organization 30.3 (2012): 326-329.

28. Wolfers, Justin. "Did unilateral divorce laws raise divorce rates? A reconciliation and new results." American Economic Review 96.5 (2006): 1802-1820.

Appendix

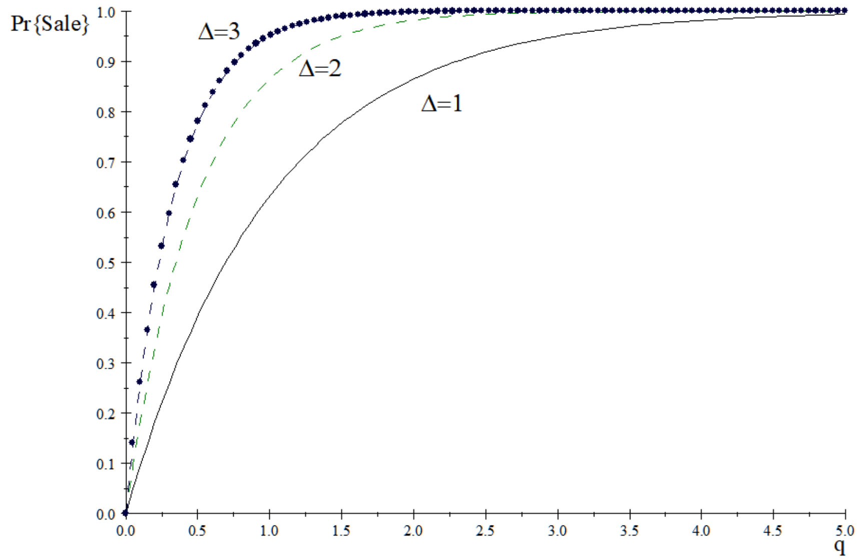


Figure 2: Illustration of the function $\Pr\{Sale_1\} = 1 - E^{-\Delta q_1}$, with $\Delta = 1, 2, 3$.

Proof of Proposition 1

We first show that in equilibrium $q_1^* < q_2^*$. Since it is not possible to algebraically calculate the equilibrium values, we resort to an alternative proof. In particular, we prove that $q_1^* < q_2^*$ by demonstrating that the reaction function of Retailer 1 $(q1(q2))$ crosses the 45 degree line at a lower value for q_2 than where the Reaction function of Retailer 2 crosses the 45 degree line. Since - as we established in the main text - both reaction functions are upward sloping, this implies that the intersection of the reaction curves is below the 45 degree line, which means that $q_2^* > q_1^*$. This is illustrated in Figure 3.

From the main text, the reaction functions are as follows:

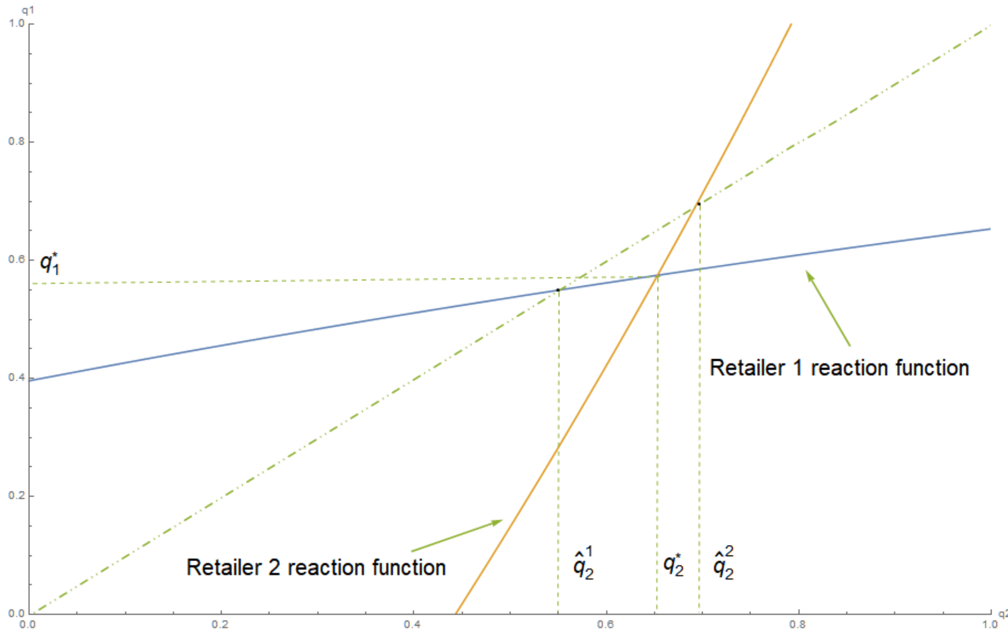


Figure 3: The intersection of the reaction functions is below the 45 degree line if $\widehat{q}_2^1 < \widehat{q}_2^2$.

$$q_1(q_2) = q_2 + t + \frac{1 - W\left(e^{\Delta(q_2+t)+1}\right)}{\Delta}, \tag{10}$$
$$q_2(q_1) = q_1 + t + 1 - \frac{W\left(e^{q_1+t+1}\right)}{\Delta},$$

We first calculate the value for q_2 at which these reaction functions intersect with the 45 degree line (with q_1 plotted on the vertical axis and q_2 on the horizontal). Let $\widehat{q}_2^1$ and $\widehat{q}_2^2$ denote the values of q_2 at which the respective reaction functions of Retailer 1 and Retailer 2 cross the 45 degree line. To obtain $\widehat{q}_2^1$ we solve $q_1(q_2) = q_2$. To obtain $\widehat{q}_2^2$ we solve $q_1^{-1}(q_2) = q_2$. We then have

$$\widehat{q}_2^1 = \frac{\ln(1 + t\Delta)}{\Delta},$$
$$\widehat{q}_2^2 = \ln(1 + t).$$

Note that $\widehat{q}_2^1 < \widehat{q}_2^2 \iff \ln(1+t\Delta) < \Delta \ln(1+t) \iff \ln(1+t\Delta) < \ln(1+t)^{\Delta} \iff 1+t\Delta < (1+t)^{\Delta} \iff \frac{1+t\Delta}{(1+t)^{\Delta}} < 1$.

The lhs of the last inequality decreases is t, since $\frac{\partial lhs}{\partial t} = -t(1+t)^{-\Delta-1}(\Delta-1)\Delta < 0$. It is therefore sufficient to show that $lhs = 1$ holds for $t = 0$. Since lhs decreases in t, any positive value of t will render $lhs < 1$. We plug $t = 0$ into lhs and get $lhs = \left.\frac{1+t\Delta}{(1+t)^{\Delta}}\right|_{t=0} = 1$. It follows that $lhs < 1$ if $t > 0$ and so $\widehat{q}_2^1 < \widehat{q}_2^2$. This in turn implies that $q_2^* > q_1^*$, Q.E.D.

Having established that $q_1^* < q_2^*$, it follows from Expression (4) that $n_1^* > n_2^*$. Q.E.D.

It is immediate from Expression (3) that $s_1^* > s_2^*$ iff $q_1^*\Delta > q_2^*$. To prove that $q_1^*\Delta > q_2^*$ it is sufficient to show that $\Delta\widehat{q}_2^1 > \widehat{q}_2^2$. This is so because $q_1(\widehat{q}_2^1) < q_1^*$ and $q_2^* < \widehat{q}_2^2$. The relationship $\Delta\widehat{q}_2^1 > \widehat{q}_2^2$ corresponds to $\ln(1+t\Delta) > \ln(1+t)$ which holds for any $\Delta > 1$. Q.E.D.

Having proven that $s_1^* > s_2^*$, we now turn to proving that $p_1^* > p_2^*$. Notice in Expression (6) that $p_i^* = s_i^* n_i^*/2t$. With $s_1^* > s_2^*$ and $n_1^* > n_2^*$ it is therefore immediate that $p_1^* > p_2^*$. Q.E.D.

We now turn to the proof of the claim that $a_1^* > a_2^*$. We can conveniently re-write Expression (2) as $a_i^* = s_i^* n_i^* p_i^*$. With $s_1^* > s_2^*$, $n_1^* > n_2^*$ and $p_1^* > p_2^*$ we therefore have $a_1^* > a_2^*$. Q.E.D.

Finally, we prove that $\Pi_1^* > \Pi_2^*$. Since $\Pi_i^* = a_i^* p_i^*$ and $a_1^* > a_2^*$ as well as $p_1^* > p_2^*$ we have $\Pi_1^* > \Pi_2^*$. Q.E.D.

Tables and Figures

Table 2: Retail Segments Covered by the Data

CapitalIQ Classification	Freq.	Percent	Cum.
Apparel Retail	494	26.21	26.21
Computer and Electronics Retail	91	4.83	31.03
Home Furnishing Retail	182	9.66	40.69
Home Improvement Retail	143	7.59	48.28
Internet and Direct Marketing Retail	494	26.21	74.48
Specialty Stores	481	25.52	100.00
Total	1,885	100.00	

Source: Selected data from S&P CapitalIQ database.

Table 3: Retail Segments Covered by the Data

CapitalIQ Classification	Mean	s.d.	Min	Max	N
REVENUES					
Apparel Retail	1565.841	2568.561	2.693	20900.440	479
Computer and Electronics Retail	736.883	793.467	0.180	3018.605	84
Home Furnishing Retail	1170.635	1837.786	14.188	11069.610	176
Home Improvement Retail	9807.566	19434.870	1.117	81804.840	137
Internet and Direct Marketing Retail	2237.261	9460.368	0.004	128820.500	456
Specialty Stores	928.527	1460.485	0.374	7532.747	442
Total	2137.657	7733.019	0.004	128820.500	1774
EBITDA					
Apparel Retail	228.229	534.283	-46.813	4662.706	477
Computer and Electronics Retail	74.036	93.517	-10.592	297.356	83
Home Furnishing Retail	154.070	286.699	-20.849	1599.52	176
Home Improvement Retail	1294.299	2609.888	-4.537	12537.94	125
Internet and Direct Marketing Retail	170.200	712.554	-154.837	11053.100	444
Specialty Stores	96.1644	164.011	-37.0434	961.570	437
Total	241.967	892.258	-154.837	12537.940	1742

Source: Selected data from S&P CapitalIQ database. Data are in EUR million, with values that were reported in other currencies converted into EUR using the exchange rate applicable at the time of reporting.

Table 4

	Online	Offline	Total
EU	19	47	66
U.S.	19	60	79
Total	38	107	145

Number of firms distributed among DDD groups.

Table 5: Post Dummy Identification

Country	Date of Implementation	$Post = 1$
Denmark	14th December 2011	2012
Finland	25th May 2011	2011
France	24th August 2011	2011
Germany	10th May 2012	2012
Greece	10th April 2012	2012
Italy	30th May 2012	2012
Poland	22nd March 2013	2013
Romania	26th July 2012	2012
Slovenia	28th December 2012	2013
Spain	2nd April 2012	2012
Sweden	1st July 2011	2011
UK	26th May 2011	2011

The table shows when Member States implemented the ePrivacy Directive 2009/136/EC. The variable *Post* takes value one from the related year onward.

Table 6: Revenues

	(1)	(2)	(3)
Dependent Variable	ln($Revenue$)	ln($Revenue$)	ln($Revenue$)
Post×Treat×Online	-0.036	-0.219**	0.011
	(0.169)	(0.103)	(0.245)
Treat×Time 2005	-0.175	-0.158	-0.180
	(0.133)	(0.149)	(0.242)
Treat×Time 2006	-0.293**	-0.256*	-0.307
	(0.118)	(0.140)	(0.207)
Treat×Time 2007	-0.213	-0.172	-0.151
	(0.144)	(0.140)	(0.291)
Treat×Time 2008	-0.056	-0.084	0.055
	(0.183)	(0.136)	(0.412)
Treat×Time 2009	-0.290**	-0.212	-0.382*
	(0.121)	(0.133)	(0.223)
Treat×Time 2010	-0.235**	-0.124	-0.410**
	(0.106)	(0.131)	(0.186)
Treat×Time 2011	-0.307***	-0.130	-0.562***
	(0.106)	(0.131)	(0.188)
Treat×Time 2012	-0.384***	-0.274	-0.581***
	(0.114)	(0.168)	(0.191)
Treat×Time 2013	-0.334***	-0.187	-0.527***
	(0.114)	(0.136)	(0.198)
Treat×Time 2014	-0.405***	-0.384**	-0.497**
	(0.127)	(0.168)	(0.224)
Treat×Time 2015	-0.569***	-0.578***	-0.637**
	(0.138)	(0.172)	(0.258)
Treat×Time 2016	-0.667***	-0.688***	-0.717**
	(0.152)	(0.191)	(0.307)
Online×Time 2005	0.133	0.403*	-0.105
	(0.197)	(0.234)	(0.314)
Online×Time 2006	0.231	0.419*	0.080
	(0.171)	(0.235)	(0.252)
Online×Time 2007	0.093	0.416*	-0.084
	(0.226)	(0.233)	(0.341)
Online×Time 2008	-0.032	0.431*	-0.244
	(0.315)	(0.221)	(0.431)
Online×Time 2009	0.126	0.303	0.007
	(0.181)	(0.211)	(0.261)
Online×Time 2010	0.431***	0.391*	0.406**
	(0.145)	(0.211)	(0.198)
Online×Time 2011	0.532***	0.416*	0.538**
	(0.162)	(0.219)	(0.226)
Online×Time 2012	0.535***	0.474**	0.513**
	(0.178)	(0.230)	(0.249)
Online×Time 2013	0.609***	0.453*	0.667**
	(0.190)	(0.232)	(0.278)
Online×Time 2014	0.579***	0.586**	0.536*
	(0.217)	(0.245)	(0.321)
Online×Time 2015	0.685***	0.681***	0.645*
	(0.241)	(0.252)	(0.356)
Online×Time 2005	0.784***	0.745***	0.778*
	(0.261)	(0.265)	(0.399)
Time FE	YES	YES	YES
Firm-specific FE	YES	YES	YES
Data	All	Large Firms	Small Firms
Observations	1,774	975	799
R-squared	0.947	0.939	0.872

Presented are OLS estimates from equation (8). Robust standard errors are reported in parenthesis below coefficient. Large firms (small firms) are those with realized revenues above (below) the sample median during the period 2004-2009. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Profits

Dependent Variable	(1) ln($EBITDA$)	(2) ln($EBITDA$)	(3) ln($EBITDA$)
Post×Treat×Online	0.221	-0.109	0.418
	(0.185)	(0.204)	(0.299)
Treat×Time 2005	-0.279	-0.003	-0.602
	(0.225)	(0.208)	(0.463)
Treat×Time 2006	-0.356*	-0.299	-0.521
	(0.215)	(0.244)	(0.411)
Treat×Time 2007	-0.222	-0.018	-0.545
	(0.207)	(0.208)	(0.419)
Treat×Time 2008	-0.019	0.152	-0.115
	(0.224)	(0.206)	(0.514)
Treat×Time 2009	-0.251	0.113	-0.629
	(0.216)	(0.204)	(0.450)
Treat×Time 2010	-0.362*	0.177	-1.023***
	(0.199)	(0.199)	(0.393)
Treat×Time 2011	-0.568***	0.054	-1.357***
	(0.205)	(0.188)	(0.407)
Treat×Time 2012	-0.528**	-0.153	-1.091***
	(0.210)	(0.233)	(0.407)
Treat×Time 2013	-0.521**	-0.077	-0.980**
	(0.221)	(0.200)	(0.430)
Treat×Time 2014	-0.485**	-0.064	-0.916*
	(0.224)	(0.208)	(0.496)
Treat×Time 2015	-0.802***	-0.492*	-1.225***
	(0.242)	(0.269)	(0.452)
Treat×Time 2016	-0.723***	-0.322	-1.350***
	(0.270)	(0.310)	(0.494)
Online×Time 2005	0.531	0.455	0.655
	(0.338)	(0.423)	(0.518)
Online×Time 2006	0.360	0.064	0.619
	(0.348)	(0.490)	(0.482)
Online×Time 2007	0.550	0.565	0.571
	(0.341)	(0.452)	(0.493)
Online×Time 2008	0.415	0.417	0.603
	(0.337)	(0.431)	(0.523)
Online×Time 2009	0.247	0.215	0.453
	(0.342)	(0.423)	(0.510)
Online×Time 2010	0.436	0.334	0.643
	(0.320)	(0.424)	(0.458)
Online×Time 2011	0.472	0.170	0.774
	(0.332)	(0.420)	(0.489)
Online×Time 2012	0.230	0.217	0.314
	(0.355)	(0.470)	(0.524)
Online×Time 2013	0.362	0.055	0.761
	(0.357)	(0.494)	(0.516)
Online×Time 2014	0.700**	0.520	1.017*
	(0.344)	(0.451)	(0.540)
Online×Time 2015	0.687*	0.657	0.827
	(0.359)	(0.478)	(0.532)
Online×Time 2016	0.515	0.495	0.568
	(0.408)	(0.549)	(0.601)
Time FE	YES	YES	YES
Firm-specific FE	YES	YES	YES
Data	All	Large Firms	Small Firms
Observations	1,561	931	630
R-squared	0.919	0.874	0.836

Presented are OLS estimates from equation (8). Robust standard errors are reported in parenthesis below coefficient.Large firms (small firms) are those with realized revenues above (below) the sample median during the period 2004-2009. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Dynamic DDD on Revenues

	Overall		Large Firms		Small Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln($Revenue$)	ln($Revenue$)	ln($Revenue$)	ln($Revenue$)	ln($Revenue$)	ln($Revenue$)
EUXOnline 2005	-0.471	-0.422	-0.392	-0.311	-0.410	-0.295
	(0.397)	(0.365)	(0.393)	(0.389)	(0.591)	(0.502)
EUXOnline 2006	-0.380	-0.350	-0.338	-0.203	-0.320	-0.281
	(0.337)	(0.332)	(0.387)	(0.390)	(0.491)	(0.477)
EUXOnline 2007	-0.404	-0.367	-0.438	-0.260	-0.219	-0.210
	(0.448)	(0.453)	(0.386)	(0.393)	(0.710)	(0.753)
EUXOnline 2008	0.061	0.079	-0.626*	-0.429	0.710	0.710
	(0.612)	(0.630)	(0.364)	(0.376)	(1.004)	(1.075)
EUXOnline 2009	-0.368	-0.364	-0.535	-0.331	-0.099	-0.164
	(0.357)	(0.360)	(0.350)	(0.365)	(0.529)	(0.541)
EUXOnline 2010	-0.452	-0.465	-0.734**	-0.539	-0.151	-0.266
	(0.280)	(0.293)	(0.345)	(0.363)	(0.408)	(0.447)
EUXOnline 2011	-0.464	-0.490*	-0.606*	-0.435	-0.248	-0.397
	(0.287)	(0.297)	(0.349)	(0.367)	(0.422)	(0.459)
EUXOnline 2012	-0.395	-0.432	-0.502	-0.371	-0.221	-0.387
	(0.300)	(0.311)	(0.374)	(0.380)	(0.436)	(0.471)
EUXOnline 2013	-0.364	-0.408	-0.678*	-0.604	-0.119	-0.286
	(0.313)	(0.318)	(0.363)	(0.382)	(0.452)	(0.484)
EUXOnline 2014	-0.242	-0.290	-0.629	-0.626	0.084	-0.068
	(0.366)	(0.373)	(0.394)	(0.400)	(0.557)	(0.586)
EUXOnline 2015	-0.229	-0.253	-0.845**	-0.939**	0.234	0.172
	(0.424)	(0.430)	(0.410)	(0.411)	(0.646)	(0.666)
EUXOnline 2016	-0.186	-0.209	-0.944**	-1.051**	0.371	0.399
	(0.474)	(0.483)	(0.437)	(0.430)	(0.746)	(0.772)
GEO Trends	NO	YES	NO	YES	NO	YES
Observations	1,774	1,774	975	975	799	799
R-squared	0.947	0.951	0.940	0.949	0.873	0.888

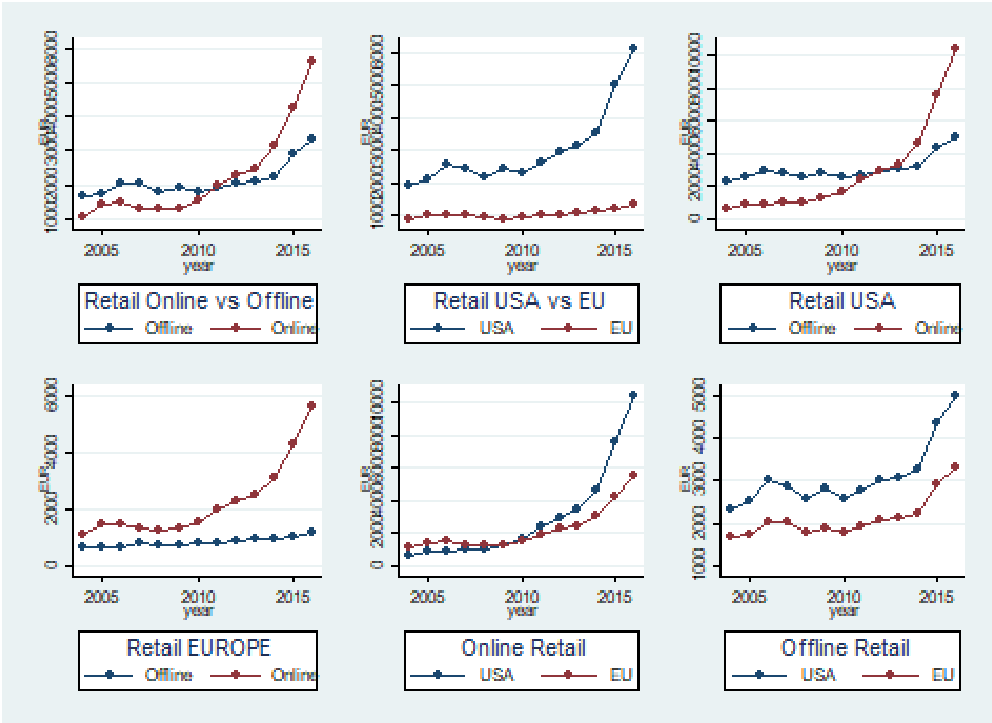
Presented are OLS estimates from equation (9) on revenues. Coefficients represent percentage variations over the base year 2004. Robust standard errors are reported in parenthesis below coefficient. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Dynamic DDD on EBITDA

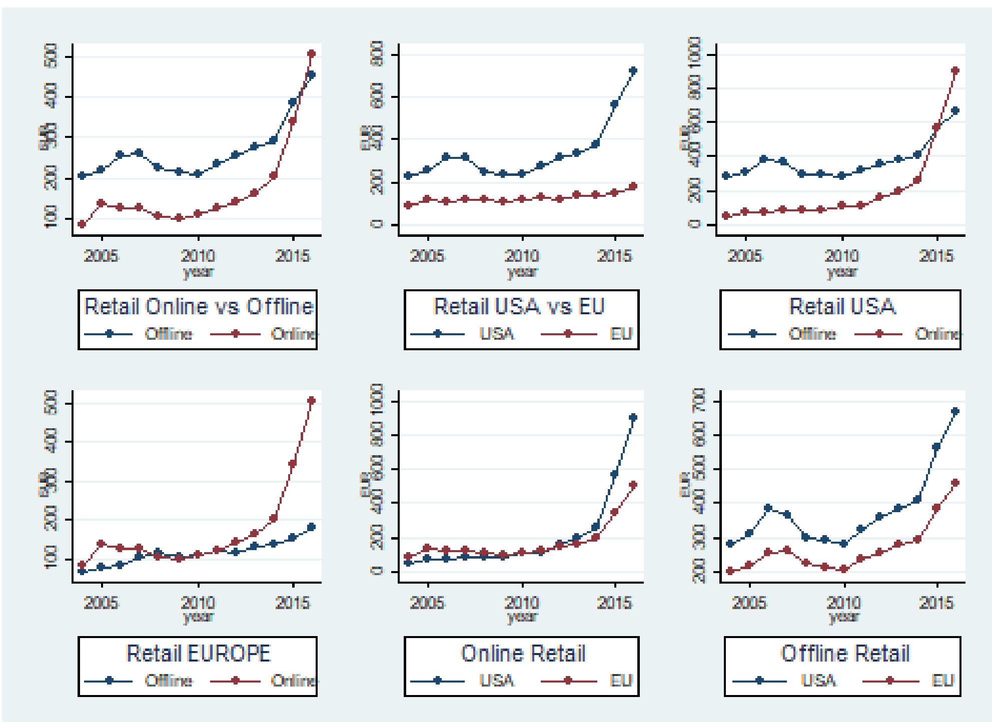
	Overall		Large Firms		Small Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln($EBITDA$)	ln($EBITDA$)	ln($EBITDA$)	ln($EBITDA$)	ln($EBITDA$)	ln($EBITDA$)
EUXOnline 2005	-0.856	-0.858	-0.177	-0.154	-1.484	-1.544
	(0.669)	(0.664)	(0.737)	(0.741)	(1.144)	(1.157)
EUXOnline 2006	-0.949	-1.007	-0.337	-0.334	-1.805*	-2.079*
	(0.688)	(0.693)	(0.908)	(0.900)	(1.081)	(1.132)
EUXOnline 2007	-1.531**	-1.687**	-0.748	-0.775	-2.244**	-2.720**
	(0.669)	(0.682)	(0.775)	(0.780)	(1.090)	(1.170)
EUXOnline 2008	-1.493**	-1.674**	-0.868	-0.904	-2.250*	-2.832**
	(0.661)	(0.667)	(0.739)	(0.751)	(1.146)	(1.214)
EUXOnline 2009	-0.967	-1.134*	-0.731	-0.777	-1.114	-1.715
	(0.675)	(0.688)	(0.727)	(0.734)	(1.162)	(1.244)
EUXOnline 2010	-1.502**	-1.661***	-1.188*	-1.251*	-1.616	-2.226**
	(0.623)	(0.639)	(0.717)	(0.721)	(1.014)	(1.125)
EUXOnline 2011	-0.961	-1.132*	-0.581	-0.666	-1.121	-1.787
	(0.626)	(0.635)	(0.694)	(0.695)	(1.033)	(1.124)
EUXOnline 2012	-1.355**	-1.528**	-0.545	-0.655	-2.002*	-2.695**
	(0.656)	(0.669)	(0.761)	(0.757)	(1.051)	(1.162)
EUXOnline 2013	-0.558	-0.746	-0.573	-0.710	-0.782	-1.458
	(0.648)	(0.660)	(0.785)	(0.795)	(1.039)	(1.161)
EUXOnline 2014	-0.972	-1.151*	-0.876	-1.087	-1.228	-1.783
	(0.639)	(0.653)	(0.748)	(0.747)	(1.098)	(1.221)
EUXOnline 2015	-0.497	-0.704	-0.615	-0.868	-0.344	-0.833
	(0.666)	(0.677)	(0.815)	(0.806)	(1.074)	(1.200)
EUXOnline 2016	-0.816	-1.036	-0.974	-1.110	-0.477	-0.783
	(0.757)	(0.764)	(0.881)	(0.915)	(1.215)	(1.318)
GEO Trends	NO	YES	NO	YES	NO	YES
Observations	1,561	1,561	931	931	630	630
R-squared	0.920	0.923	0.875	0.879	0.840	0.858

Presented are OLS estimates from equation (9) on EBITDA. Coefficients represent percentage variations over the base year 2004. Robust standard errors are reported in parenthesis below coefficient. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 4: Trends Over Categories



(a) Average Revenue Over Categories



(b) Average EBITDA Over Categories

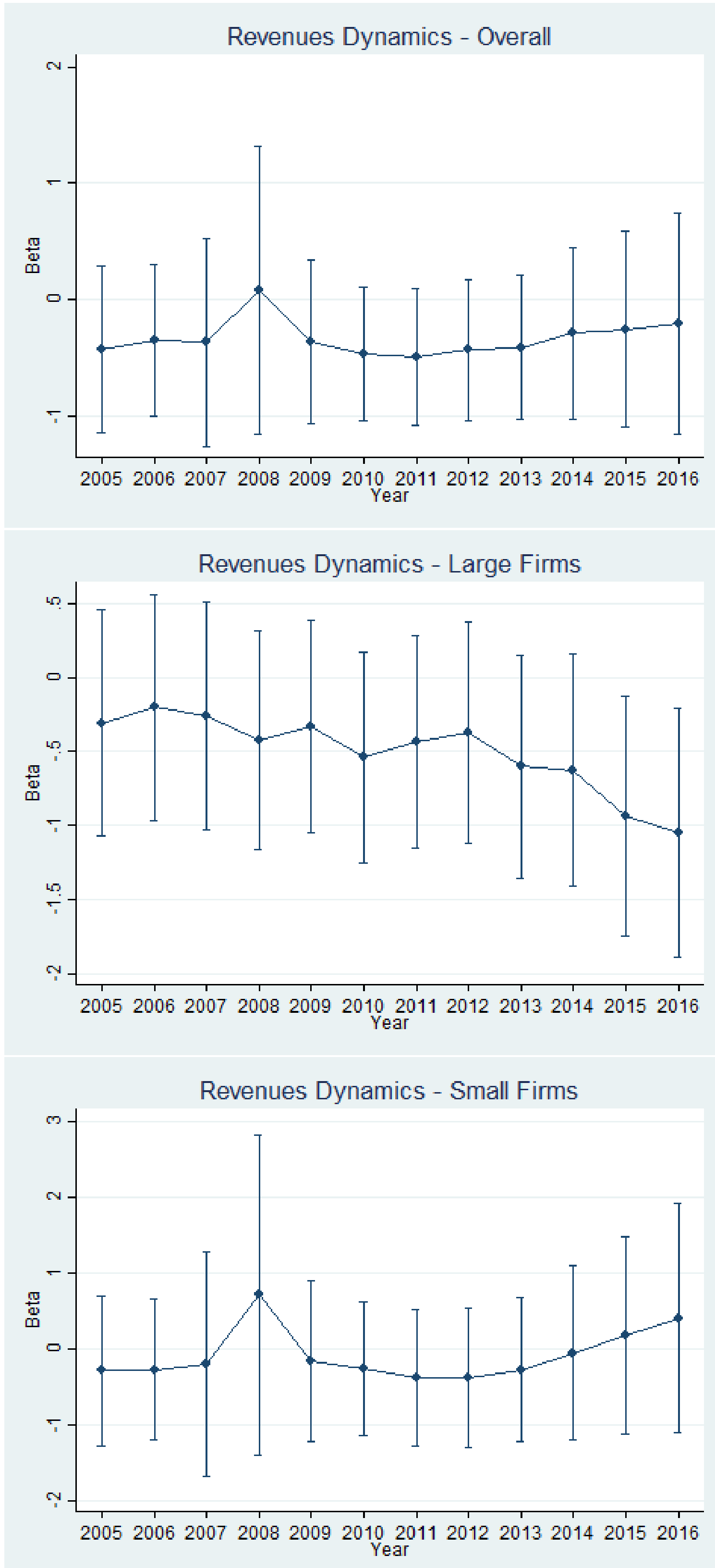


Figure 5: The figure plots the regression coefficients from Table 8 columns 2-4-6, capturing the dynamic impact of the ePrivacy Directive on the logarithm of revenues of the firms in our sample. Each period corresponds to a year, with 2004 being the base year. The 95 percent confidence interval is based on robust standard errors.

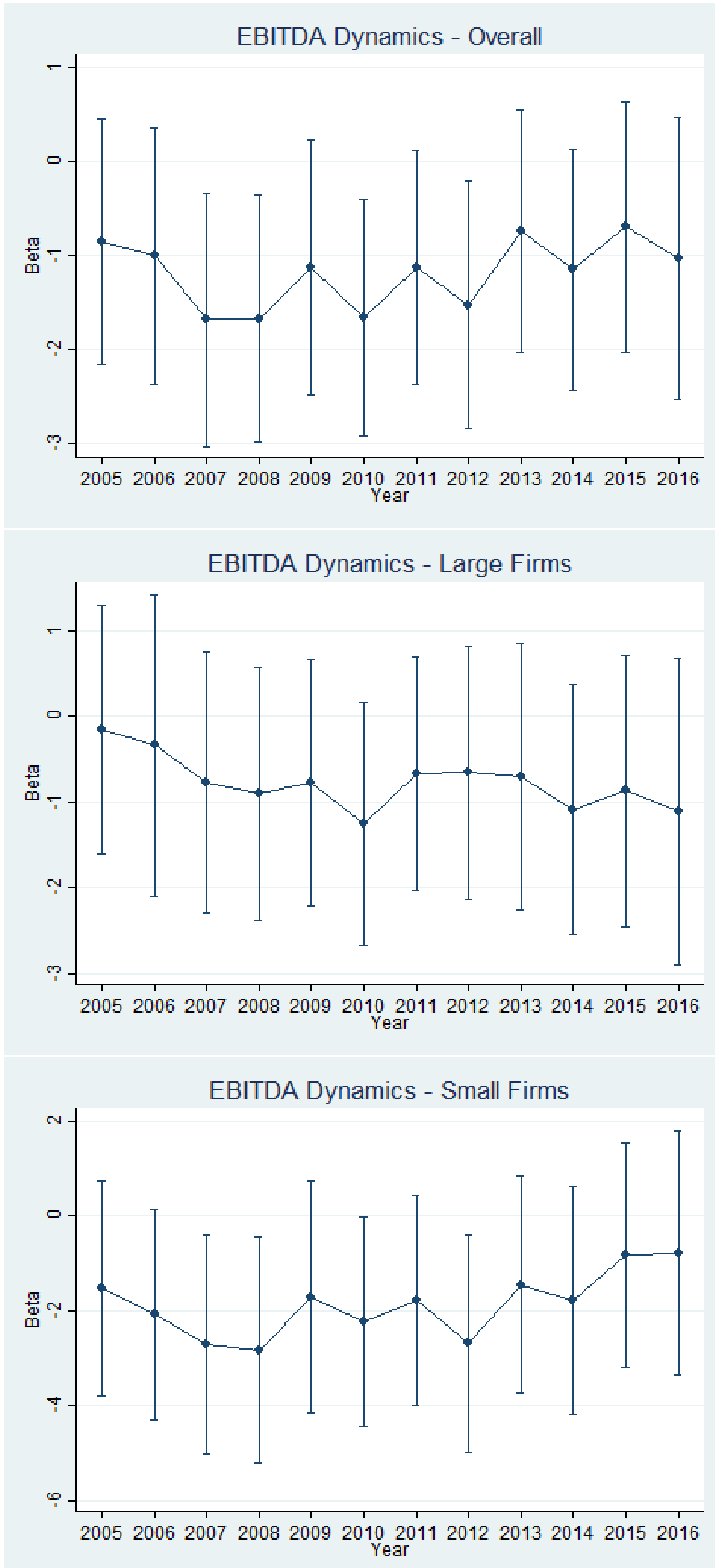


Figure 6: The figure plots the regression coefficients from Table 9 columns 2-4-6, capturing the dynamic impact of the ePrivacy Directive on the logarithm of EBITDA of the firms in our sample. Each period corresponds to a year, with 2004 being the base year. The 95 percent confidence interval is based on robust standard errors.

Notes

[1]Recently, the 2018 General Data Protection Regulation (GDPR) empowered European data protection authorities to issue hefty fines comparable to those in antitrust on firms violating data protection rules.

[2]As an executive of Adform, a leading independent advertising technology company, put it: "*for the other [small] players, advertising revenues will diminish as cross-platform reach via tracking & measurement, essential for providing Advertising success metrics, will slowly die. Only if you are big enough with respect to reach (and potentially still data), you will be able to attract advertising budgets. If you are a medium or small publisher, you are likely out of that game. As a result, the walled gardens will grow even stronger, they will increase their dominance of the Internet; even fewer players will own even more data*". Source: https://www.linkedin.com/pulse/eprivacy-welcome-end-internet-jochen-schlosser.

[3]*Cookies* are small files placed by visited websites on the users computer that allows the website to track the users activity and use this information for segmenting audience and make targeted offers.

[4]We follow Reinganum (1983) and a large body of subsequent R&D literature with this functional form assumption. The Annex contains a graphical illustration of the function $s_i(q_i)$.

[5]A recent survey by Episerver (2018) found that only 17 percent of people say that making a purchase is their primary purpose for visiting a brand's website for the first time. The primary purpose of visiting an e-commerce website is in the vast majority of cases is not directly related to purchase intent, but involves looking for information on store openings, shipping or payment. It therefore seems unlikely that consumers would strategically refrain from website visits anticipating that doing so may affect prices.

[6]This relationship is confirmed in a series of ordered probit regressions, explaining website privacy scores by the number of monthly users. The result holds largely also when taking individual privacy categories as dependent variable. The regression outputs are available upon request from the authors.

[7]Early applications of this approach are found in Ashenfelter and Card (1984), Card (1992), and Card and Krueger (1993).

[8]This is crucial in our analysis, since EU firms are in principle much more similar to each other than US firms.

[9]As shown in Table 5 in next Section, the ePrivacy Directive 2009/136/EC has been implemented between 2011 and 2013.

[10]As shown by Goodman-Bacon (2018), the resulting estimate is a weighted average of all the simple two-period treatment effects in each DDD, where the weights depend on treatment variances and group sizes.

[11]As shown in next Section, we select firms that realize alt least 80% of their revenues in one specific country.

[12]Each firm in our sample operates in one geographical market, either USA or one of the EU Member States. The inclusion of geographic-specific time trends allow us to control for preexisting economic trends affecting the countries where our firms operate, and follows the empirical strategy developed by Wolfers (2006).

[13]Not surprisingly, when we perform a DiD on European firms, where offline firms belong to the control group, we find a strong positive effect of the policy change on both revenues and profits.

[14]The implementation dates were taken from national laws and publicly available documents. The full list of sources is available upon request.

[15]Large firms are defined by those with realized revenues above the sample median before the implementation of the ePrivacy Directive.

[16]Recall that the coefficient of interest in Tables 6 and 7 measure the average percentage variation of the dependent variable on the treated when the policy change is in place against the period when it is not.

PREVIOUS DISCUSSION PAPERS

308 Sabatino, Lorien and Sapi, Geza, Online Privacy and Market Structure: Theory and Evidence, February 2019.

307 Izhak, Olena, Extra Costs of Integrity: Pharmacy Markups and Generic Substitution in Finland, January 2019.

306 Herr, Annika and Normann, Hans-Theo, How Much Priority Bonus Should be Given to Registered Organ Donors? An Experimental Analysis, December 2018.
Forthcoming in: Journal of Economic Behavior and Organization.

305 Egger, Hartmut and Fischer, Christian, Increasing Resistance to Globalization: The Role of Trade in Tasks, December 2018.

304 Dertwinkel-Kalt, Markus, Köster, Mats and Peiseler, Florian, Attention-Driven Demand for Bonus Contracts, October 2018.

303 Bachmann, Ronald and Bechara, Peggy, The Importance of Two-Sided Heterogeneity for the Cyclicality of Labour Market Dynamics, October 2018.

302 Hunold, Matthias, Hüschelrath, Kai, Laitenberger, Ulrich and Muthers, Johannes, Competition, Collusion and Spatial Sales Patterns – Theory and Evidence, September 2018.

301 Neyer, Ulrike and Sterzel, André, Preferential Treatment of Government Bonds in Liquidity Regulation – Implications for Bank Behaviour and Financial Stability, September 2018.

300 Hunold, Matthias, Kesler, Reinhold and Laitenberger, Ulrich, Hotel Rankings of Online Travel Agents, Channel Pricing and Consumer Protection, September 2018 (First Version February 2017).

299 Odenkirchen, Johannes, Pricing Behavior in Partial Cartels, September 2018.

298 Mori, Tomoya and Wrona, Jens, Inter-city Trade, September 2018.

297 Rasch, Alexander, Thöne, Miriam and Wenzel, Tobias, Drip Pricing and its Regulation: Experimental Evidence, August 2018.

296 Fourberg, Niklas, Let's Lock Them in: Collusion under Consumer Switching Costs, August 2018.

295 Peiseler, Florian, Rasch, Alexander and Shekhar, Shiva, Private Information, Price Discrimination, and Collusion, August 2018.

294 Altmann, Steffen, Falk, Armin, Heidhues, Paul, Jayaraman, Rajshri and Teirlinck, Marrit, Defaults and Donations: Evidence from a Field Experiment, July 2018.
Forthcoming in: Review of Economics and Statistics.

293 Stiebale, Joel and Vencappa, Dev, Import Competition and Vertical Integration: Evidence from India, July 2018.

292 Bachmann, Ronald, Cim, Merve and Green, Colin, Long-run Patterns of Labour Market Polarisation: Evidence from German Micro Data, May 2018.
Forthcoming in: British Journal of Industrial Relations.

291 Chen, Si and Schildberg-Hörisch, Hannah, Looking at the Bright Side: The Motivation Value of Overconfidence, May 2018.

290 Knauth, Florian and Wrona, Jens, There and Back Again: A Simple Theory of Planned Return Migration, May 2018.

289 Fonseca, Miguel A., Li, Yan and Normann, Hans-Theo, Why Factors Facilitating Collusion May Not Predict Cartel Occurrence – Experimental Evidence, May 2018.
Published in: Southern Economic Journal, 85 (2018), pp. 255-275.

288 Benesch, Christine, Loretz, Simon, Stadelmann, David and Thomas, Tobias, Media Coverage and Immigration Worries: Econometric Evidence, April 2018.

287 Dewenter, Ralf, Linder, Melissa and Thomas, Tobias, Can Media Drive the Electorate? The Impact of Media Coverage on Party Affiliation and Voting Intentions, April 2018.
Forthcoming in: European Journal of Political Economy.

286 Jeitschko, Thomas D., Kim, Soo Jin and Yankelevich, Aleksandr, A Cautionary Note on Using Hotelling Models in Platform Markets, April 2018.

285 Baye, Irina, Reiz, Tim and Sapi, Geza, Customer Recognition and Mobile Geo-Targeting, March 2018.

284 Schaefer, Maximilian, Sapi, Geza and Lorincz, Szabolcs, The Effect of Big Data on Recommendation Quality. The Example of Internet Search, March 2018.

283 Fischer, Christian and Normann, Hans-Theo, Collusion and Bargaining in Asymmetric Cournot Duopoly – An Experiment, October 2018 (First Version March 2018).
Published in: European Economic Review, 111 (2019), pp.360-379.

282 Friese, Maria, Heimeshoff, Ulrich and Klein, Gordon, Property Rights and Transaction Costs – The Role of Ownership and Organization in German Public Service Provision, February 2018.

281 Hunold, Matthias and Shekhar, Shiva, Supply Chain Innovations and Partial Ownership, February 2018.

280 Rickert, Dennis, Schain, Jan Philip and Stiebale, Joel, Local Market Structure and Consumer Prices: Evidence from a Retail Merger, January 2018.

279 Dertwinkel-Kalt, Markus and Wenzel, Tobias, Focusing and Framing of Risky Alternatives, December 2017.
Forthcoming in: Journal of Economic Behavior and Organization.

278 Hunold, Matthias, Kesler, Reinhold, Laitenberger, Ulrich and Schlütter, Frank, Evaluation of Best Price Clauses in Online Hotel Booking, December 2017 (First Version October 2016).
Published in: International Journal of Industrial Organization, 61 (2019), pp. 542-571.

277 Haucap, Justus, Thomas, Tobias and Wohlrabe, Klaus, Publication Performance vs. Influence: On the Questionable Value of Quality Weighted Publication Rankings, December 2017.

276 Haucap, Justus, The Rule of Law and the Emergence of Market Exchange: A New Institutional Economic Perspective, December 2017.
Published in: von Alemann, U., D. Briesen & L. Q. Khanh (eds.), The State of Law: Comparative Perspectives on the Rule of Law, Düsseldorf University Press: Düsseldorf 2017, pp. 143-172.

275 Neyer, Ulrike and Sterzel, André, Capital Requirements for Government Bonds – Implications for Bank Behaviour and Financial Stability, December 2017.

274 Deckers, Thomas, Falk, Armin, Kosse, Fabian, Pinger, Pia and Schildberg-Hörisch, Hannah, Socio-Economic Status and Inequalities in Children’s IQ and Economic Preferences, November 2017.

273 Defever, Fabrice, Fischer, Christian and Suedekum, Jens, Supplier Search and Re-matching in Global Sourcing – Theory and Evidence from China, November 2017.

272 Thomas, Tobias, Heß, Moritz and Wagner, Gert G., Reluctant to Reform? A Note on Risk-Loving Politicians and Bureaucrats, October 2017.
Published in: Review of Economics, 68 (2017), pp. 167-179.

271 Caprice, Stéphane and Shekhar, Shiva, Negative Consumer Value and Loss Leading, October 2017.

270 Emch, Eric, Jeitschko, Thomas D. and Zhou, Arthur, What Past U.S. Agency Actions Say About Complexity in Merger Remedies, With an Application to Generic Drug Divestitures, October 2017.
Published in: Competition: The Journal of the Antitrust, UCL and Privacy Section of the California Lawyers Association, 27 (2017/18), pp. 87-104.

269 Goeddeke, Anna, Haucap, Justus, Herr, Annika and Wey, Christian, Flexibility in Wage Setting Under the Threat of Relocation, September 2017.
Published in: Labour: Review of Labour Economics and Industrial Relations, 32 (2018), pp. 1-22.

268 Haucap, Justus, Merger Effects on Innovation: A Rationale for Stricter Merger Control?, September 2017.
Published in: Concurrences: Competition Law Review, 4 (2017), pp.16-21.

267 Brunner, Daniel, Heiss, Florian, Romahn, André and Weiser, Constantin, Reliable Estimation of Random Coefficient Logit Demand Models, September 2017.

266 Kosse, Fabian, Deckers, Thomas, Schildberg-Hörisch, Hannah and Falk, Armin, The Formation of Prosociality: Causal Evidence on the Role of Social Environment, July 2017.

265 Friehe, Tim and Schildberg-Hörisch, Hannah, Predicting Norm Enforcement: The Individual and Joint Predictive Power of Economic Preferences, Personality, and Self-Control, July 2017.
Published in: European Journal of Law and Economics, 45 (2018), pp. 127-146.

264 Friehe, Tim and Schildberg-Hörisch, Hannah, Self-Control and Crime Revisited: Disentangling the Effect of Self-Control on Risk Taking and Antisocial Behavior, July 2017.
Published in: European Journal of Law and Economics, 45 (2018), pp. 127-146.

263 Golsteyn, Bart and Schildberg-Hörisch, Hannah, Challenges in Research on Preferences and Personality Traits: Measurement, Stability, and Inference, July 2017.
Published in: Journal of Economic Psychology, 60 (2017), pp. 1-6.

262 Lange, Mirjam R.J., Tariff Diversity and Competition Policy – Drivers for Broadband Adoption in the European Union, July 2017.
Published in: Journal of Regulatory Economics, 52 (2017), pp. 285-312.

261 Reisinger, Markus and Thomes, Tim Paul, Manufacturer Collusion: Strategic Implications of the Channel Structure, July 2017.

260 Shekhar, Shiva and Wey, Christian, Uncertain Merger Synergies, Passive Partial Ownership, and Merger Control, July 2017.

259 Link, Thomas and Neyer, Ulrike, Friction-Induced Interbank Rate Volatility under Alternative Interest Corridor Systems, July 2017.

258 Diermeier, Matthias, Goecke, Henry, Niehues, Judith and Thomas, Tobias, Impact of Inequality-Related Media Coverage on the Concerns of the Citizens, July 2017.

257 Stiebale, Joel and Wößner, Nicole, M&As, Investment and Financing Constraints, July 2017.

256 Wellmann, Nicolas, OTT-Messaging and Mobile Telecommunication: A Joint Market? – An Empirical Approach, July 2017.

255 Ciani, Andrea and Imbruno, Michele, Microeconomic Mechanisms Behind Export Spillovers from FDI: Evidence from Bulgaria, June 2017.
Published in: Review of World Economics, 153 (2017), pp. 704-734.

254 Hunold, Matthias and Muthers, Johannes, Spatial Competition with Capacity Constraints and Subcontracting, October 2018 (First Version June 2017 under the title "Capacity Constraints, Price Discrimination, Inefficient Competition and Subcontracting").

253 Dertwinkel-Kalt, Markus and Köster, Mats, Salient Compromises in the Newsvendor Game, June 2017.
Published in: Journal of Economic Behavior and Organization, 141 (2017), pp. 301-315.

252 Siekmann, Manuel, Characteristics, Causes, and Price Effects: Empirical Evidence of Intraday Edgeworth Cycles, May, 2017.

251 Benndorf, Volker, Moellers, Claudia and Normann, Hans-Theo, Experienced vs. Inexperienced Participants in the Lab: Do they Behave Differently?, May 2017.
Published in: Journal of the Economic Science Association, 3 (2017), pp.12-25.

250 Hunold, Matthias, Backward Ownership, Uniform Pricing and Entry Deterrence, May 2017.

249 Kreickemeier, Udo and Wrona, Jens, Industrialisation and the Big Push in a Global Economy, May 2017.

248 Dertwinkel-Kalt, Markus and Köster, Mats, Local Thinking and Skewness Preferences, April 2017.

247 Shekhar, Shiva, Homing Choice and Platform Pricing Strategy, March 2017.

246 Manasakis, Constantine, Mitrokostas, Evangelos and Petrakis, Emmanuel, Strategic Corporate Social Responsibility by a Multinational Firm, March 2017.
Published in: Review of International Economics, 26 (2018), pp. 709-720.

245 Ciani, Andrea, Income Inequality and the Quality of Imports, March 2017.

244 Bonnet, Céline and Schain, Jan Philip, An Empirical Analysis of Mergers: Efficiency Gains and Impact on Consumer Prices, February 2017.

243 Benndorf, Volker and Martinez-Martinez, Ismael, Perturbed Best Response Dynamics in a Hawk-Dove Game, January 2017.
Published in: Economics Letters, 153 (2017), pp. 61-64.

242 Dauth, Wolfgang, Findeisen, Sebastian and Suedekum, Jens, Trade and Manufacturing Jobs in Germany, January 2017.
Published in: American Economic Review, Papers & Proceedings, 107 (2017), pp. 337-342.

Older discussion papers can be found online at:
http://ideas.repec.org/s/zbw/dicedp.html

Heinrich-Heine-University of Düsseldorf

**Düsseldorf Institute for
Competition Economics (DICE)**

Universitätsstraße 1 _ 40225 Düsseldorf
www.dice.hhu.de

ISSN 2190-9938 (online)
ISBN 978-3-86304-307-0