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Abstract

Exploiting the timing and territorial scope of the European Union's General Data Protection Regulation (GDPR), this paper examines how privacy regulation shaped firm performance in a large sample of companies across 61 countries and 34 industries. Controlling for firm and country-industry-year unobserved characteristics, we compare the outcomes of firms at different levels of exposure to EU markets, before and after the enforcement of the GDPR in 2018. We find that enhanced data protection had the unintended consequence of reducing the financial performance of companies targeting European consumers. Across our full sample, firms exposed to the regulation experienced a 8% decline in profits, and a 2% reduction in sales. An exception is large technology companies, which were relatively unaffected by the regulation on both performance measures. Meanwhile, we find the negative impact on profits among small technology companies to be almost double the average effect across our full sample. Following several robustness tests and placebo regressions, we conclude that the GDPR has had significant negative impacts on firm performance in general, and on small companies in particular.

Keywords: privacy regulation, GDPR, firm performance, patenting, innovation

JEL classification: L5, O3, M3

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1 Introduction

Personal data is an important factor of production in modern economies. It is also a contentious topic for governments and policy makers seeking to balance the data privacy concerns of citizens against the vitality of their economies. Against this background, the European Union passed the General Data Protection Regulation (GDPR) in April 2016. The regulation, which came into force in May 2018, now governs the processing of EU residents' personal data. The key objective was to give individuals more control over their data, which makes it harder and more expensive for companies to commercialize it. Thus, while the GDPR has received much praise for safeguarding the data rights of individuals, concerns have been raised over its consequences for European competitiveness. In the words of Axel Voss, a member of the European Parliament, "Europe's obsession with data protection is getting in the way of digital innovation".[1]

So far, however, the GDPR has largely been implemented in an empirical vacuum. While previous studies have investigated the effects of privacy regulation on online activity and technology ventures (Aridor et al., 2020; Jia et al., 2021), there is little systematic evidence on how companies have fared and responded to the GDPR beyond the technology sector.[2] In addition, by focusing on online outcomes, the existing literature leaves out compliance costs and potential adverse effects on firm performance and innovation. This could hide the broader impacts of the GDPR and deliver a misleading picture to policymakers interested in its potential unintended consequences.

To fill this empirical void, we examine the impact of the GDPR on firms profits and sales across 35 industries comprising all sectors of the economy in 61 countries. For our

[1]Voss, A. (2021). How to bring GDPR into the digital age. Politico, March 25.

[2]A growing literature investigates the impact of privacy regulation on *online outcomes* (Goldberg et al., 2021; Aridor et al., 2020; Johnson et al., 2020). However, as emphasised by Goldberg et al. (2021), one problem with online outcomes is that their measurement is likely biased, precisely because individuals might not consent websites to record their data following the introduction of the new privacy rules.

empirical analysis, we use an unbalanced panel of 698,124 patenting firms from ORBIS IP between 2011 and 2020. Because companies operating in the EU are subject to the GDPR regardless of where they are incorporated, the global coverage of the ORBIS database makes it particularly suitable for our purpose of analyzing the impact of the GDPR on firm performance. To establish an appropriate control group, we create a novel measure of companies exposure to the GDPR based on inter-industry linkages, using data from the OECD Inter-Country Input-Output (ICIO) Tables. For each 2-digit industry-country pair, we calculate the share of output sold to European markets and use this share to quantify how exposed firms are to the regulation. An important advantage of this approach is that it allows us to control for time-varying, country-industry unobserved heterogeneity, which accounts for potential pre-trends in firms' performance within specific industries.

The GDPR might in principle affect firm performance in two ways. First, it requires companies to develop GDPR compliant processes and technologies, which creates costs and reduces profits. Second, as users incur a cost when prompted to give consent to using their data, they might reduce online purchases, leading to lower sales. Our baseline estimates suggest that, on average, firms operating in the EU experienced a 8% reduction in profits, and a 2% decrease in sales, in response to the enforcement of the GDPR in 2018, which implies that the regulation adversely impacted firm performance primarily through the cost channel. We also provide evidence that the main burden of the GDPR has fallen on smaller companies. This is especially true in technology industries, where the decline in profits of small companies is almost double the average across our full sample.[3] This reduction in profits, we note, corresponds to a marked acceleration in patenting, especially among small technology companies, which we hypothesize reflects efforts to develop GDPR-compliant

[3]The negative impact on small firms might be due to the limited resources they can allocate to compliance with privacy regulation (Brill, 2011). Another reason might be that by offering a restricted range of services, they find it more difficult obtaining users' consent (Goldberg et al., 2021; Campbell et al., 2015).

technologies. Meanwhile, we find no statistically significant impacts on either profits or sales among large IT services providers, like Facebook, Microsoft, Amazon, and Google.[4] To probe these relationships further, we perform several placebo exercises in which we replace our enforcement dummy with alternative year dummies. Reassuringly, these robustness checks do not pick up preexisting trends unrelated to the GDPR that might drive our results.

Our paper relates to two literatures. First, a growing body of work examines the economic effects of the GDPR. For instance, Goldberg et al. (2021) find that the GDPR adversely impacted web traffic and e-commerce sales, while Aridor et al. (2020) provide evidence that it decreased consumer traffic in the online travel industry. In addition, Johnson et al. (2020) show that data privacy regulation reduced data sharing online, but had the unintended consequence of increasing market concentration among web technology vendors. Finally, Jia et al. (2021) document a negative impact of the GDPR on venture capital and angel investments in technology companies. What these studies have in common is that they focus on individual industries, and mostly on online outcomes. We add to this literature by providing the first systematic evidence of the impacts of the GDPR on companies total sales and profits across all sectors of the economy.

Second, while it has been recognised that privacy regulation might affect innovation (Goldfarb and Tucker, 2012), the empirical literature has so far focused on the *adoption* of specific technologies in healthcare, showing that privacy regulation, which restricts the ability of hospitals to release health information, reduced their adoption of data-intensive medical technologies (Miller and Tucker, 2009, 2011, 2018). In contrast, we examine the effects of data privacy on *innovation*, documenting an increase in patenting in response to the enforcement of the GDPR in technology industries.

[4] We note that these findings are consistent with those of Johnson et al. (2020), Peukert et al. (2020) and Lefrere et al. (2020), showing that the GDPR increased (online) market concentration, to the benefit of large IT service providers.

The remainder of this paper is structured as follows. Section 2 provides an overview of the GDPR. Section 3 describes our data and empirical approach. Section 4 presents the results of estimating the impact of the GDPR on firm performance. Section 5 zooms in on technology industries, exploring how IT services providers have fared from the GDPR. Finally, in section 6, we outlines some conclusions.

2 The General Data Protection Regulation

Firms operating within the European Union are subject to its General Data Protection Regulation (GDPR), which establishes the rules for how the personal data of EU residents may be processed, including browser cookies and IP addresses. The GDPR also applies to firms that are incorporated outside EU countries, provided they target consumers that live in the European Union. While the regulation was passed in April 2016, it only became enforceable in May 2018, giving companies two years to adjust to changes being introduced. The objective underpinning its adoption was to give individuals more control over their personal data, while at the same time encouraging companies to limit their use of such data for activities like marketing. By specifying the legal basis under which a company may or may not process personal data, the GDPR affects companies in several ways (Johnson et al., 2020). For example, since its introduction, websites are prohibited from sharing user data with third parties, without the consent from each user, and valid consent must be affirmative, which makes data collection more costly and reduces companies' ability to extract personal data. It also gives EU residents the right to access, update, correct, delete, and port their personal data, meaning that firms wanting to process personal data must invest in building, inventing or buying IT systems that fulfil people's rights. In addition, companies that target EU residents are required to encrypt and anonymise any personal data it stores, and must audit their internal data processes to ensure compliance. This includes appointing a data protection officer to oversee data management activities. The compliance costs imposed on companies are in other words significant, especially for those whose business model relies on the processing of personal data. According to PwC (2018), some companies have spent over 10 million EUR annually on GDPR compliance alone since the law became enforceable in May 2018.

However, the cost of failing to comply can be even larger. Fines for non-compliance can reach the larger amount of 20 million EUR or 4 percent of global revenue. By applying fines to global revenue, rather than revenue from EU countries, the GDPR incentivises multinationals targeting EU residents to abide by its rules, even if most revenue is generated elsewhere. Large fines have already been leveraged on a number of companies across a host of industries, including Google (50 million EUR), H&M (35 million), Telecom Italia (27.8 million), British Airways (22 million), and Marriott (20.4 million). We note that between January 2020 and 2021, the data protection authorities recorded 121,165 data breach notifications—an increase by 19 percent from the previous year. Over the same period, GDPR fines rose by nearly 40 percent (DLA Piper, 2021).[5]

In the light of these costs, we conclude that there are compelling incentives for companies to reduce their processing of personal data in response to the adoption of the GDPR. We proceed to investigating its effects on firms' performance across the globe.

3 Data and Methodology

In the below, we describe the construction of our dataset, discuss our measurement of companies exposure to the GDPR, and outline our empirical strategy.

[5] https://www.dlapiper.com/en/us/insights/publications/2021/01/dla-piper-gdpr-fines-and-data-breach-survey-2021/

3.1 Firm Data

For our analysis, we construct a firm-level dataset from ORBIS IP (ORBIS hereafter), provided by the Bureau Van Dijk. In addition to providing matched patent data for a large number of companies around the world, ORBIS also contains information from companies balance sheets and financial statements, including sales, employment and profits. Because companies in a wide range of non-EU countries are also exposed to the GDPR (Figure 1), the global coverage of the ORBIS database makes it particularly suitable for our purpose of exploring the GDPR effect on firm performance.

Bajgar et al. (2020) has examined the coverage and representativeness of the balance sheets' information provided by ORBIS in great detail. They show that the ORBIS database suffers from one important limitation, which is that the firms in the dataset are disproportionately large, old, and productive. This means that we have good coverage of large top-performing firms but an under-representation of firms at the bottom-end of the productivity distribution. Another concern is that firms appearing and disappearing in the dataset reflects changes in coverage rather than actual entry and exit. For our purposes, however, these drawbacks are not major concerns since we are interested in average within-firm changes in outcomes, as opposed to business dynamics and changes in the size distribution of companies.

We begin by performing extensive data cleaning following Kalemli-Ozcan et al. (2019) and Bajgar et al. (2020).[6] This approach yields an unbalanced panel of 698,124 patenting firms operating in 35 2-digit industries and 61 countries for the period 2011 to 2020, leaving us with 3,562,190 observations. In terms of annual coverage, every year between 2011 and 2018 includes approximately 10% of total observations. For the year 2019, this figure somewhat declines to around 7%, while 2020 contains only 0.3% of our sample.

[6] See Appendix OB 1 for a detailed description of the data cleaning procedure.

Based on our empirical strategy, outlined in equation (1), this gives us two years of good data coverage to identify the impact of the GDPR. It also means that we do not have to be concerned about potential confounding effects from the COVID-19 pandemic. If we restrict our sample so that each firm has non-missing observations for all outcome variables considered, we end up with 392,379 firms and 1,332,456 observations. This is due to the fact that many firms do not report gross profits, which is a key variable in our analysis below. In this sample, the incidence of EU firms is approximately 5%. This is not an issue in itself, because as shown in Figure 1, there is substantial variation in the exposure to EU markets for non-EU firms.

3.2 Exposure to the GDPR

We next seek to quantify the impact of the GDPR on firms that are subject to the regulation, which also applies to entities that are incorporated outside the European Union, provided that they target potential customers that live in EU countries. To capture the extent to which companies target EU residents, we construct a novel GDPR exposure measure based on information on trade flows across 36 2-digit ISIC Rev. 4 industries and 64 countries, from the OECD Inter-Country Input-Output (ICIO) Tables.[7] The ICIO Tables are similar to standard input-output tables. However, they also include cross-country industry data on imports and exports.[8] For each country-industry pair, we calculate the share of output sold to EU countries, which we denote by $S_{c,i}^{EU}$. We set 2010 as the base year and use the corresponding file from the ICIO repository.

Figure 1 presents $S_{c,i}^{EU}$ by country, distinguishing between EU and non-EU countries.

[7]While the underlying data are based on 819 industries, the ICIO Tables merge these in to broader categories. In ORBIS, there are no firms in industry ISIC rev. 4 D90T96 "Arts, entrateinment, recreation and other service activities". Therefore, our sample includes a total of 35 industries.

[8]The diagonal blocks of the ICIO Tables are standard input-output tables, while the off-diagonal blocks represent inter-country flows.

Unsurprisingly, EU countries generally trade more with their counterparts in the EU. Yet, several non-EU countries also have significant trading relationships with the EU, meaning that they are potentially affected by the GDPR. We further note that there is significant variation in the share of output sold in the EU across non-EU countries, which we next turn to exploit, allowing us to pin down the impact of the GDPR on firms sales and profits.

Finally, it must be noted that while the regulation was passed in April 2016, it only became enforceable in May 2018, giving companies two years to adjust to the changes being introduced. To capture the timing of the regulation, we multiply $S_{c,i}^{EU}$ with a dummy taking the value 1 from 2018 onward, $1\{t \geq 2018\}$. Thus, we follow a large literature using the timing of regulatory enforcement as an event study (Watzinger et al., 2020; Lu and Yu, 2015; Aghion et al., 2009; Lu et al., 2017; Autor et al., 2006; Moser and Voena, 2012). Specifically, we define the variable $GDPR_{c,i,t}$, which measures exposure to the GDPR for firms in each 2-digit industry i in country c as:

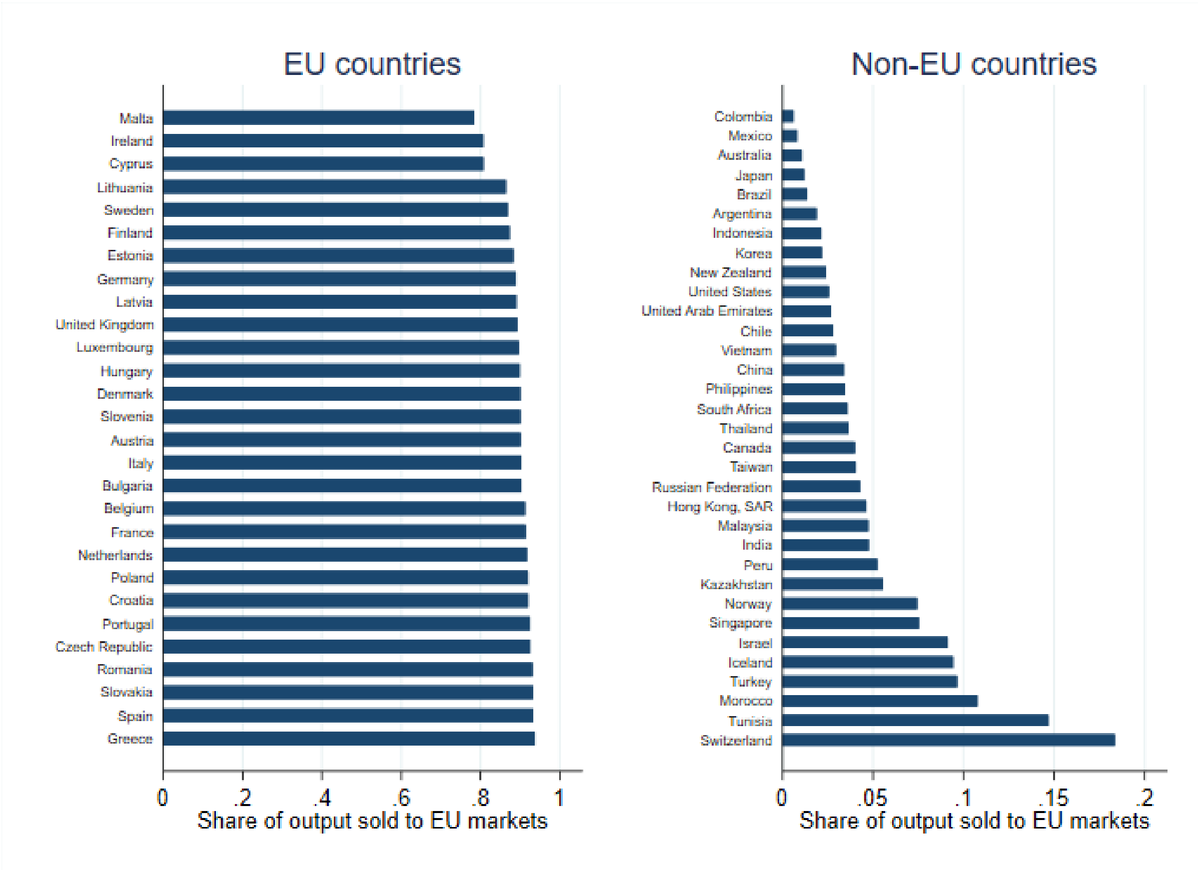
$$GDPR_{c,i,t} \equiv S_{c,i}^{EU} \cdot 1\{t \geq 2018\} \tag{1}$$

3.3 Empirical Strategy

As noted in Section 2, the GDPR might have a substantial impact on firms' *costs*. A virtue of our dataset is that we also have information on gross profits, which allows us to capture compliance costs, unlike the existing literature which focuses more narrowly on the revenue impact of the GDPR or relies proxies of sales based on online activity (Aridor et al., 2020; Goldberg et al., 2021; Johnson et al., 2020). Specifically, we run the following regression:

$$Y_{f,c,i,t} = \beta_0 + \beta_1 \, GDPR_{c,i,t} + u_f + u_{c,j,t} + \varepsilon_{f,c,i,t} \tag{2}$$

Figure 1: Share of output supplied to EU28 countries, by country.



The figure shows the country-level average share of output sold to EU markets in the base year (2010). Sources: ICIO, OECD

where $Y_{f,c,i,t}$ represents an outcome of firm f, operating in country c, within a 2-digit industry i, in year t. The term $GDPR_{c,i,t} = S_{c,i}^{EU} \cdot 1\{t \geq 2018\}$ is a "shift-share" variable and identification of β_1 is based on differential firm-level outcomes before and after 2018 (the "shift") for firms operating in country-industry pairs with varying exposure to EU markets (the "share"). Thus, our identification strategy is based on the assumption that firms in the country-2-digit industry pairs most exposed to EU markets are not differentially affected by other shocks or trends.[9] However, since EU countries trade predominantly with each other, firms in 2-digit industries within the EU might well be particularly exposed to the GDPR. Hence, if the performance of EU firms differs systematically from other companies because of EU policies other than the GDPR, or EU-specific economic shocks, this would make our identification strategy problematic.

To address such concerns, we include in model (2) country-1-digit industry-year fixed effects, $u_{c,j,t}$, where 1-digit industries are indexed by j. The inclusion of such fixed effects allows us to safely compare firms across countries and broadly-defined industries. However, country-2-digit industry-specific trends (or more granular ones) could still affect our estimates.[10] Ideally, we would want to include more narrowly-defined country-industry-year fixed effects. However, this is not possible because it would completely absorb the impact of our shift-share variable, which varies at the country-2-digit-year level. To that end, in Section 4.2, we perform a battery of diagnostic tests and robustness checks to examine the validity of our identification assumption, showing that our estimates hold across a host of specifications.

We further note that in addition to absorbing unrelated shocks, the inclusion of country-1-digit industry-year fixed effects absorbs the impact of different currencies and country-industry-specific price deflators. It also alleviates the potential endogeneity in the timing of policy adoption and enforcement (i.e., non-random treatment timing), although the adoption of the GDPR is unlikely to be driven by concerns over economic performance, as the EU recognized the need for data protection already in 1995, when it passed the European Data Protection Directive in response to the proliferation of the Internet. Since $GDPR_{c,i,t}$ varies at the country-2-digit-industry-level, we cluster errors accordingly across

[9] We are only concerned about shocks and trends, since time-invariant unobserved confounders are absorbed by the firm fixed effects. Moreover, given the diff-in-diff design implied by (2), the impact of confounders affecting all firms equally in a given 2-digit industry would not affect our estimates.

[10] For instance, the textile industry in the EU might be shrinking due to growing competition from Asia.

all specifications.

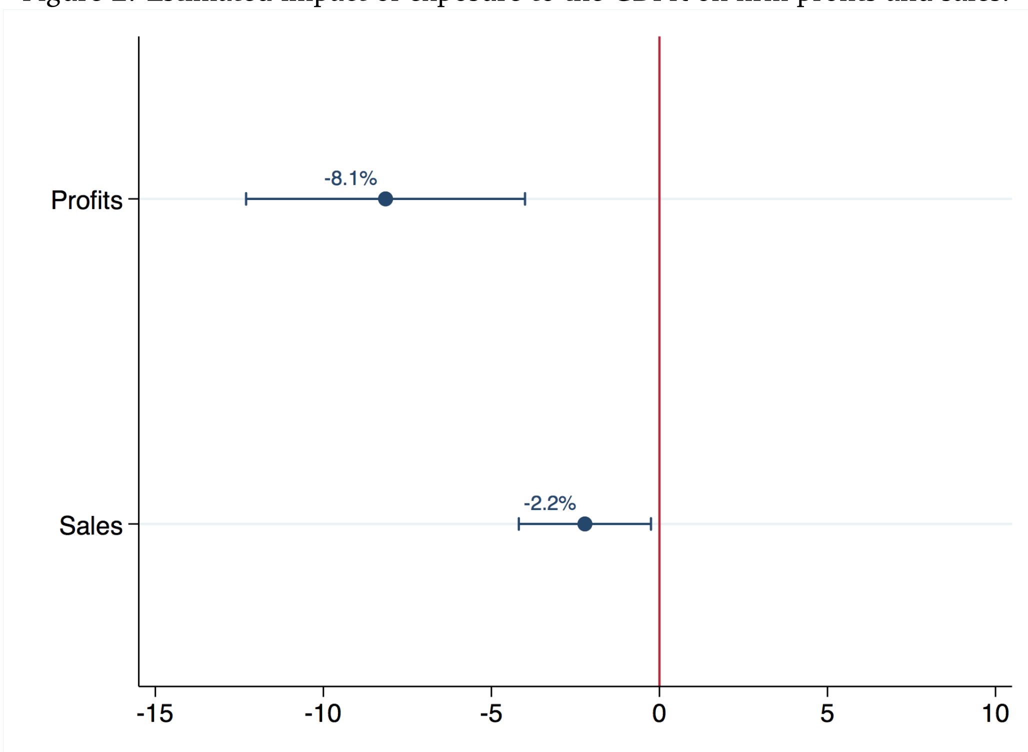
4 The GDPR and Firm Performance

In principle, there are two key channels through which the implementation of the GDPR can affect firm performance: i) by adding compliance costs, or ii) if users incur a cost when prompted to give consent to using their data, then there might be a reduction in online purchases. Compliance costs naturally reduce profits, but do not necessarily affect sales. A reduction in online purchases, in contrast, would certainly reduce sales.

We next turn to exploring the impacts of the GDPR through these channels. Figure 2 provides a first glance at our main results, which are obtained by estimating equation 2 and computing average marginal effects.[11] It provides point estimates and 90% confidence intervals for the effect of the GDPR on profits and sales. Turning first to profits, we note that the coefficient is negative and statistically significant. Our estimates suggest that, on average, exposed firms experienced 8% reduction in profits in response to the enforcement of the GDPR in 2018. The sales coefficient is also negative and statistically significant, but smaller in magnitude. On average, firms experienced a decline in sales of roughly 2% following the introduction of the regulation. Taken together, our findings suggest that the GDPR reduced firm performance primarily through the cost channel, rather than by reduced online activity putting downward pressure on sales. Such an interpretation is consistent with the findings of Zhuo et al. (2021), showing that online activity did not decrease significantly after the GDPR came into force. We next turn to probing these findings in greater detail.

[11]The regression results are presented in columns 1 and 2 of Table A1. The average marginal effect is computed by multiplying the coefficients in Table A1 with the sample average value of $S_{c,i}^{EU}$, which is 0.065.

Figure 2: Estimated impact of exposure to the GDPR on firm profits and sales.



The figure presents average marginal effects of the GDPR on log-profits and log-sales. The average marginal effect is computed by multiplying the coefficients in Table A1 with the sample average value of $S_{c,i}^{EU}$, which is 0.065. The point estimates are included in 90% confidence intervals.

4.1 Threats to Validity

As noted, a key concern with our identification assumption is that firms in the country-2-digit industries most exposed to EU markets are also differentially affected by other shocks or trends. For example, Goldsmith-Pinkham et al. (2020) show that when identification is based on differential exposure to a common shock, as in our case, a sufficient condition for consistent inference on β_1 is that the share-component of the instrument is as good as randomly assigned. In our specific framework, the sufficient condition is that differences in exposure to EU markets across 2-digit industries in 2010 should not be correlated to firm-level outcomes after 2010. However, this assumption does not hold in general. For instance, non-EU firms in export-intensive industries (i.e., with high exposure to EU markets) might be more productive than others (De Loecker and Warzynski, 2012). Therefore, one would expect a positive correlation between exposure to EU markets and firm performance. Conversely, EU firms in industries with high exposure to EU markets (i.e., with limited involvement in extra-EU trade) might be less productive than others. If that is the case, one would expect a negative correlation between EU market exposure and firm performance.

The top panel of Figure OA 1 shows that there is indeed a positive correlation between exposure and log-profits for non-EU firms, and that the correlation is negative for their EU counterparts.[12] Hence, we include the full set of fixed effects as in equation 2. This allows us to remove both the time-invariant correlation between the *level* of firm outcomes and 2-digit industry characteristics (including exposure to EU markets), as well as the potential correlation between the level of firm outcomes and country-industry shocks or pre-trends. The sufficient condition for consistent identification of β_1 can thus be reformulated in less demanding terms of orthogonality between exposure and *changes* in firm outcomes. To

[12] To improve the readability of the figure, we plot median values in each country and 2-digit industries.

assess whether this condition holds in our data, the bottom panel of Figure OA 1 presents the correlation between exposure and the residual of a regression of log-profits on the full set of fixed effects. We note that the relationship between the two series becomes flat, which suggests that conditional on firm fixed effects, exposure to EU28 markets does not predict firm performance. As a result, the share component $S_{c,i}^{EU}$ can be considered as good as randomly assigned and we can consistently estimate β_1 in equation 2. We also observe a very similar pattern in Figure OA 2, when we focus on sales.

4.2 Further Robustness

To check more directly whether our estimate might be affect by pre-trends, we run a placebo test in which we replace $1\{t \geq 2018\}$ with a dummy taking value 1 for the year 2016, 2014, or 2012. Table OA 1 presents the findings from this exercise. We note that our design picks up a negative trend in profits already in 2016 (column 1), when the GDPR was passed, but not on sales (column 2). This is not surprising since firms will have incurred compliance costs well in advanced of the actual enforcement of the regulation. Indeed, the very purpose of making the GDPR enforceable only from 2018 was to give firms time to adjust and invest in becoming compliant. Equally reassuring is the absent impact on sales in 2016. As noted, the mandatory elicitation of data sharing only came into force in 2018. Turning to columns 3-6, we do not find any significant effect with the alternative dummies $1\{t \geq 2014\}$ and $1\{t \geq 2012\}$, as expected. This suggests that our baseline estimates do not simply pick up confounding pre-trends.

Still, since we rely on yearly data, our identification might attribute changes in firm performance that are unrelated to the GDPR after 2018.[13] For example, our shifter $1\{t \geq$

[13] Unlike existing work on the GDPR, which uses weekly variation in online data (Aridor et al., 2020; Johnson et al., 2020), we can only exploit yearly variation. However, our approach has the advantage of examining the impact of the GDPR on a much broader set of industries and outcomes relative to the existing studies.

$2018\}$ might capture the impact of Brexit (Sampson, 2017), or the Trump tariffs (Amiti et al., 2019). The bias would be especially severe if such unobserved shocks were disproportionately affecting EU firms, as they might spill over to non-EU companies with the strongest trading relationships with the EU. We address this concern by including a full set of EU-4-digit industry-year fixed effects. This allows us to purge our estimates from narrowly-defined industry trends that are specific to EU firms. This is an important test, as EU industrial and trade policies are likely to affect firms in specific industries. The results are presented in Table OA 2. We note that the coefficient for profits is similar in magnitude to our baseline estimates and statistically significant, while the sales coefficient loses significance.

As a further robustness check, we estimate model (2) with the inclusion of EU demand shifters. Specifically, we use $S_{\tilde{c},i}^{EU}$, where $\tilde{c}$ indexes non-EU countries, and then aggregate the change in EU real value added using these shares:

$$\Delta VA_{\tilde{c},i,t} \equiv S_{\tilde{c},i}^{EU} \cdot \ln \frac{VA_t^{EU}}{VA_{t-1}^{EU}}$$

For this exercise, we naturally exclude European firms, whose performance is endogenous to the EU demand shifter, from the sample. Table OA 3 presents the results. We note that the demand shifters are not statistically significant, which suggests that the full set of fixed effects absorbs industry-level developments related to shocks in the EU region. The coefficient for profits is again very similar to our baseline estimates, while the coefficient for sales is negative but again not statistically significant.

We next control for potential time-varying confounders at the micro-level by including in model (2) two key company variables: the log of the capital stock and the log of employment. As shown in Table OA 4, both capital and labor exhibit positive relationships with profits as well as sales.[14] But their inclusion only reduces the GDPR effect on profits very slightly, while the sales coefficient remains statistically insignificant. Taken together, these results underline our key finding: that most adverse impacts of the GDPR on firm performance have occurred through the cost channel.

Finally, there is a concern that our results are driven by a specific country or group of countries. In particular, one might worry that the entry of Chinese firms, which surged in our sample around 2018, could drive our estimates. To that end, in Table OA 5, we drop all Chinese companies, which reassuringly delivers similar results (columns 1-2). Moreover, in columns 3-4, we exclude all non-OECD countries, which again confirms our baseline estimates. Our key findings are also robust to dropping the United States (columns 5-6), as well as all EU countries (columns 7-8). Dropping EU countries, however, results in a negative and significant impact on profits, but not on sales (coeff. = -0.303; s.e. = 0.231), as Table OA 3 shows. We note that the same asymmetric impact on profits and sales holds in columns 9-10, when we drop all OECD countries.

4.3 Large *vs* Small Firms

While our results so far show that the GDPR has reduced firm performance on average, they are silent about its impact by firm size. As is well-known, large firms typically have more technical and financial resources to comply with regulations (Brill, 2011), but they are also more able to obtain consent for personal data processing from individual consumers (Goldfarb and Tucker, 2011). Thus, it stands to reason that small companies might be disproportionately negatively affected by the regulation.

To explore this, we construct a dummy variable $SMALL_f = 1$ if a company has less than 500 employees in the base year, or the first year in which a firm appears in our dataset.

[14]Due to missing observations for companies capital stock, the number of observations in Table OA 4 is lower than in the baseline.

We then interact it with $GDPR_{c,i,t}$ in the following way:[15]

$$Y_{f,c,i,t} = \beta_0 + \beta_1\, GDPR_{c,i,t} + \beta_2\, GDPR_{c,i,t} \times SMALL_f + u_f + u_{c,j,t} + \varepsilon_{f,c,i,t} \tag{3}$$

Figure 3 presents the average marginal effects with point estimates and 90% confidence intervals.[16] The left panel presents the GDPR effect on log-profits by firm size. We note that the coefficients are negative and significant for both large and small companies. We further note that they are of similar magnitude, although the profits of small firms are roughly 1 percentage point lower. Turning to the impact on sales, in the left side panel of Figure 3, we note that both large and small companies experienced sales declines in response to the implementation of the GDPR. However, the negative average impact on sales, presented in Figure 2, appears to be primarily driven by firms with less than 500 employees. For large firms, the coefficient is negative but not statistically significant at conventional levels. These findings speak to the theoretical results of Campbell et al. (2015), which suggest that if users incur a cost when prompted to give consent to using their data, and large firms offer a wider range of products or services, then small companies should be the most adversely affected in terms of sales.[17] Whether we look at sales or profits, the main burden of the GDPR has fallen on smaller companies.

[15]To avoid potential endogeneity concerns, for firms entering the dataset after the base year, we drop the first observation.

[16]The regression results are presented in Table A2. The average marginal effect on large firms is computed by multiplying β_1 with the sample average value of $S^{EU}_{c,i}$, which is 0.065. The average marginal effect for small firms is computed as the linear combination $0.065 \times (\hat{\beta}_1 + \hat{\beta}_2)$.

[17]This is because a user seeking to purchase a basket of products is more likely to visit and making purchases on the website of a large firm in order to pay the cost only once, rather than giving consent to several small specialised websites.

Figure 3: Estimated impact of exposure to the GDPR on firm profits and sales: large *vs* small firms

The figure presents average marginal effects of the GDPR on log-profits and log-sales. Small firms are those with less than 500 employees. The average marginal effect on large firms is computed by multiplying β_1 in Equation (3) with the sample average value of $S_{c,i}^{EU}$, which is 0.065. The average marginal effect for small firms is computed as the linear combination $0.065 \times (\hat{\beta}_1 + \hat{\beta}_2)$. The point estimates are included in 90% confidence intervals.

5 Technology Companies

We next zoom in on information technology companies, which should arguably be most affected by the regulation. Indeed, an important aspect of the GDPR is that websites are prohibited from sharing user data without explicit consent from third parties. In other words, IT services providers, like Apple and Facebook, which process user data for marketing activities (Johnson et al., 2020), should face higher costs for their inputs. By making data collection more costly, the GDPR might reduce the quantity of user data available to technology industries, thereby adversely affecting their economic performance.

5.1 Firm Performance

We identify IT services providers (or technology firms for brevity) as those operating in NACE Rev. 2 industries J62 "Computer programming, consultancy and related activities" and J63 "Information service activities". For our analysis, we construct a dummy $IT_f = 1$ if a firm is in one of those industries. This allows us to explore the GDPR effect on companies like Google and Adobe, but also smaller technology companies. Specifically, we estimate models based on the following specification:

$$Y_{f,c,i,t} = \beta_0 + \beta_1 \, GDPR_{c,i,t} + \beta_2 \, GDPR_{c,i,t} \times IT_f + u_f + u_{c,j,t} + \varepsilon_{f,c,i,t} \tag{4}$$

Like in the previous section, we quantify the impact of the GDPR on the most exposed IT service providers by computing the average marginal effects and 90% confidence intervals. To elucidate whether larger technology companies have fared differently from their competitors, we also specifically account for small IT services providers by including the triple interaction $GDPR_{c,i,t} \times IT_f \times SMALL_f$. Our results are reported graphically in Figure 4.[18] Unlike for the average firm, we find no evidence that the GDPR has reduced the profits or sales of large IT firms. The coefficients for profits and sales are negative, but not statistically significant. Turning to small technology firms, with fewer than 500 employees, we note that the coefficient for profits and sales are both negative, although the coefficient for sales is not statistically significant at conventional levels (p-value = 0.14). Strikingly, the decline in profits for technology firms is 4 percent higher than the average (Figure 2). Instead, the decline in sales is similar to the average. Our findings broadly speak to those of Johnson et al. (2020), showing that following the introduction of the GDPR, the largest IT services providers gained market shares at the expenses of their smaller competitors.

We conclude that the impact of the GDPR in technology industries has been quantitatively larger on profits relative to sale in general (Figure 4), and on small companies in particular. While ORBIS does not provide a detailed breakdown of companies operating expenses (e.g., data on R&D expenditure or purchases of IT services and equipment is highly limited or unavailable), we next use patent data to capture these firms efforts to develop GDPR-compliant processes and technologies, which might partly account for the reduction in profits.[19]

5.2 Patenting

Though there is widespread concern that the GDPR has reduced digital innovation in Europe, it is equally plausible that it has accelerated innovation by inducing companies to develop new GDPR-compliant technologies. Taking a closer look at some recent patent documents, we note that these include applications for technologies like a "System and

[18] The regression results are presented in Table A3.

[19] Since non-technology companies are likely to buy GDPR-compliant technologies rather than develop them internally, and ORBIS does not entail information on IT purchases, we restrict our analysis to patenting in technology industries. The impact of the GDPR on patenting across all 35 industries yield similar, but less precisely estimated coefficients, suggesting that the aggregate effect is driven by technology industries. Tables are available upon request.

Figure 4: Estimated impact of exposure to the GDPR on firm profits and sales: IT firms.

The figure presents average marginal effects of the GDPR on log-profits and log-sales. IT firms are firms in NACE Rev. 2 industries J62 "Computer programming, consultancy and related activities" and J63 "Information service activities". Small firms have less than 500 employees in 2010 or in the first year of observation after 2010. The point estimates are included in 90% confidence intervals.

method for providing general data protection regulation (GDPR) compliant hashing in blockchain ledgers", which guarantees a user's right to be forgotten in compliance with the GDPR. Another example is a "Data Consent Manager", displayed in Figure OA 3, which is a computer implemented method for managing consent for sharing data. The patent document notes that failing to comply with the GDPR "can result in adverse consequences for any persons or organizations found to be mishandling data", which the technology sets out to mitigate.

Against this background, we explore how the GDPR has shaped companies inventive efforts in the technology sector more broadly. For this part of our analysis, we use data on companies flows of patent applications.[20] Crucially, for each patent application, ORBIS provides a unique identifier for the applying firm. This allows us to track companies and their patent applications each year. However, since only a subset of all patenting companies report information on its industry of operation and number of employees—both needed to implement our empirical specification (4)—we are only able to match 50% of the total number of patenting companies in ORBIS.

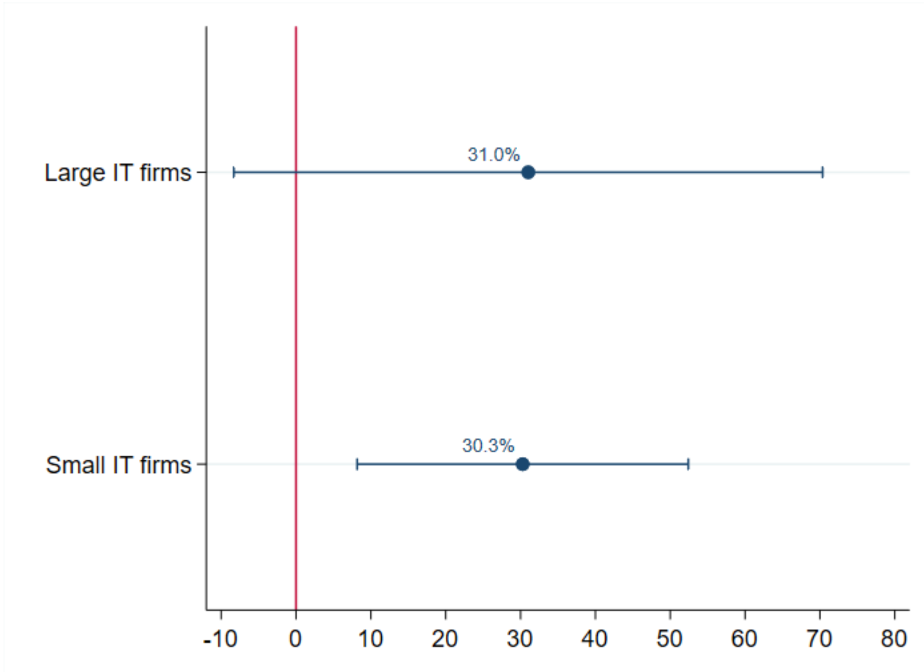
Figure 5 presents the results from this reduced sample of patenting companies.[21] We note that the average marginal effects of the GDPR on patenting among technology companies is positive and equal to 30 percent.[22] While the impact of the GDPR on patenting among large IT service providers is imprecisely estimated, the impact for small technology firms is significant at the 95 percent confidence level. The relatively large investments in new technologies by smaller companies speaks to Figure 4, showing that small IT companies have seen their profits being reduced most substantially by the GDPR. Whether the increase in patenting, which we argue reflects adjustment to the new regulatory environment, will lead to higher productivity growth in the future, is a topic we have to leave for future research.

[20] We focus on patent flows since the stock of patent also reflects past inventive efforts.

[21] The detailed estimation results can be found in Table A4.

[22] As before, the average marginal effect is obtained by multiplying the coefficients in Table A4 by the sample average value of $S_{c,i}^{EU}$, which is 0.065. To express the impact in percentage terms, we divide the average marginal effect by the sample average number of patent applications, which is 18.877.

Figure 5: Estimated impact of exposure to the GDPR on patent applications.



The figure presents average marginal effects of the GDPR on patent applications by IT firms. IT firms are those in NACE Rev. 2 industries J62 "Computer programming, consultancy and related activities" and J63 "Information service activities". Small firms have less than 500 employees in 2010 or in the first year of observation after 2010. The point estimates are included in 90% confidence intervals.

6 Conclusions

The GDPR has been celebrated globally. According to The New York Times, for example, the new privacy law makes Europe "the world's leading tech watchdog." In Silicon Valley, leading technology companies have been forced to comply with the new regulation to be able to target customers in Europe. Meanwhile, countries like Brazil, Canada and South Korea have followed suit, passing similar data protection laws beginning in 2020. "If we can export this [the GDPR] to the world, I will be happy", Vera Jourova, the European commissioner in charge of data privacy, who helped draft the regulation, recently explained.[23]

Given that the GDPR is swiftly becoming the blueprint for privacy protection globally, understanding its economic consequences is crucial. To the best of our knowledge, this paper provide the first systematic evidence on the impact of the GDPR on firm performance across all sectors of the economy. Our analysis builds on the simple intuition that the GDPR can affect firm performance in two ways: either by adding compliance costs, or by lowering sales, if users incur a cost when prompted to give consent to using their data. While we find both channels to be quantitatively important, the cost channel consistently dominates across all specifications. On average, across our full sample, firms operating in the EU experienced a 8% reduction in profits, but only a 2% decrease in sales. Thus, previous studies, which have focused on online outcomes or proxies of sales, provide an incomplete picture by not considering profits, which have been more adversely affected through surging compliance costs.

We further find that companies have fared differently from the GDPR. For example, the negative profit impact among small companies in information technology is double the average effect across our full sample. In contrast, we find no significant impacts on large IT services providers, like Facebook, Apple and Google, on both performance measures. This might seem somewhat surprising, since big tech has reportedly deployed large teams to overhaul their privacy settings and to redesign certain products to become GDPR-compliant. Indeed, Facebook says it has added some 1,000 engineers, managers, and lawyers globally in response to the new regulation. Meanwhile, LobbyFacts.eu, which tracks spending on lobbying, estimate that Google, Facebook and Apple now rank among the five biggest corporate spenders on lobbying in the European Union, all with budgets

[23] Satariano, A. (2018). G.D.P.R., a New Privacy Law, Makes Europe World's Leading Tech Watchdog. The New York Times, May 24.

above 3.5 million EUR.[24] Also, according to the same watchdog site, Facebook doubled its lobbying budget in 2017 on the previous year, following the passage of the GDPR.

Thus, to many observers, the impact of the GDPR on the fortunes of big tech may seem ambiguous. As The New York Times writes, "Whether Europe's tough approach is actually crimping the global tech giants is unclear... Amazon, Apple, Google and Facebook have continued to grow and add customers".[25] In this paper, we are able to shed some light on this issue, showing that despite significant compliance costs, large technology companies have not experienced any statistically significant declines in sales or falling profits as a consequence of the GDPR. Instead, the main burden has fallen on small companies. These results speak to the findings of Johnson et al. (2020) and Peukert et al. (2020), showing that the GDPR increased (online) market concentration. Large technology companies have gained market share from their smaller competitors, offsetting the compliance costs associated with the GDPR.

Still, our findings must interpreted with caution. First, the GDPR has only recently become enforceable and the negative impacts on firm performance we observe may partly reflect temporary adjustment costs, meaning that its effects might taper-off in the future. For example, the large increase in patenting in response to the regulation, documented above, is likely to reflect one-off investments in new GDPR-compliant technologies, which will put downward pressure on profits in the short-run. Second, if the GDPR gradually becomes a global standard as more countries adopt similar regulations, companies targeting EU companies will become less disadvantaged over time. Finally, while we find that the GDPR has had large negative impacts on firm performance, it must be noted that our estimates are silent on its aggregate welfare effects, which must also account for potential

[24] https://lobbyfacts.eu/reports/lobby-costs/all/0/2/2/2/21/0/

[25] Satariano, A. (2018). G.D.P.R., a New Privacy Law, Makes Europe World's Leading Tech Watchdog. The New York Times, May 24.

benefits to citizens concerned with data protection. We deem this to be a fruitful future line of inquiry.

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Appendix

Table A1: Exposure to the GDPR, firm-level profits and sales.

	(1) Profits	(2) Sales
Exposure to GDPR	-1.255***	-0.341*
	(0.389)	(0.184)
Observations	1,332,456	1,332,456
R-squared	0.687	0.944
Firm FE	yes	yes
Country x 1-dig-industry x year FE	yes	yes

The table shows OLS estimates based on 2. The dependent variables are expressed in logs. Exposure to the GDPR is the 2010 (base year) share of output sold to European countries in each country-2-digit industry pair, and interacted with a dummy taking value 1 from 2018 onward. Standard errors are clustered at the country-2-digit industry-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A2: Exposure to the GDPR, firm-level profits and sales: large *vs* small firms.

	(1) Profits	(2) Sales
Exposure to GDPR	-1.214***	-0.293
	(0.396)	(0.188)
Exposure to GDPR $\times$ small	-0.101	-0.119**
	(0.108)	(0.051)
Observations	1,332,456	1,332,456
R-squared	0.687	0.944
Firm FE	yes	yes
Country x 1-dig-industry x year FE	yes	yes

The table shows OLS estimates based on 3. The dependent variables are expressed in logs. Exposure to the GDPR is the 2010 (base year) share of output sold to European countries in each country-2-digit industry pair, and interacted with a dummy taking value 1 from 2018 onward. Small firms have less than 500 employees in 2010 or in the first year of observation after 2010. Standard errors are clustered at the country-2-digit industry-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A3: Exposure to the GDPR, firm-level profits and sales: IT services providers.

	(1) Profits	(2) Sales
Exposure to GDPR	-1.263***	-0.339*
	(0.389)	(0.184)
Exposure to GDPR $\times$ IT	0.553	0.230**
	(0.375)	(0.113)
Exposure to GDPR $\times$ IT $\times$ small	-1.155**	-0.210
	(0.533)	(0.151)
Observations	1,332,456	1,332,456
R-squared	0.687	0.944
Firm FE	yes	yes
Country x 1-dig-industry x year FE	yes	yes

The table shows OLS estimates based on 4. The dependent variables are expressed in logs. Exposure to the GDPR is the 2010 (base year) share of output sold to European countries in each country-2-digit industry pair, and interacted with a dummy taking value 1 from 2018 onward. IT firms are firms in NACE Rev. 2 industries J62 "Computer programming, consultancy and related activities" and J63 "Information service activities" from the OECD ICIO tables. Small firms have less than 500 employees in 2010 or in the first year of observation after 2010. Standard errors are clustered at the country-2-digit industry-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

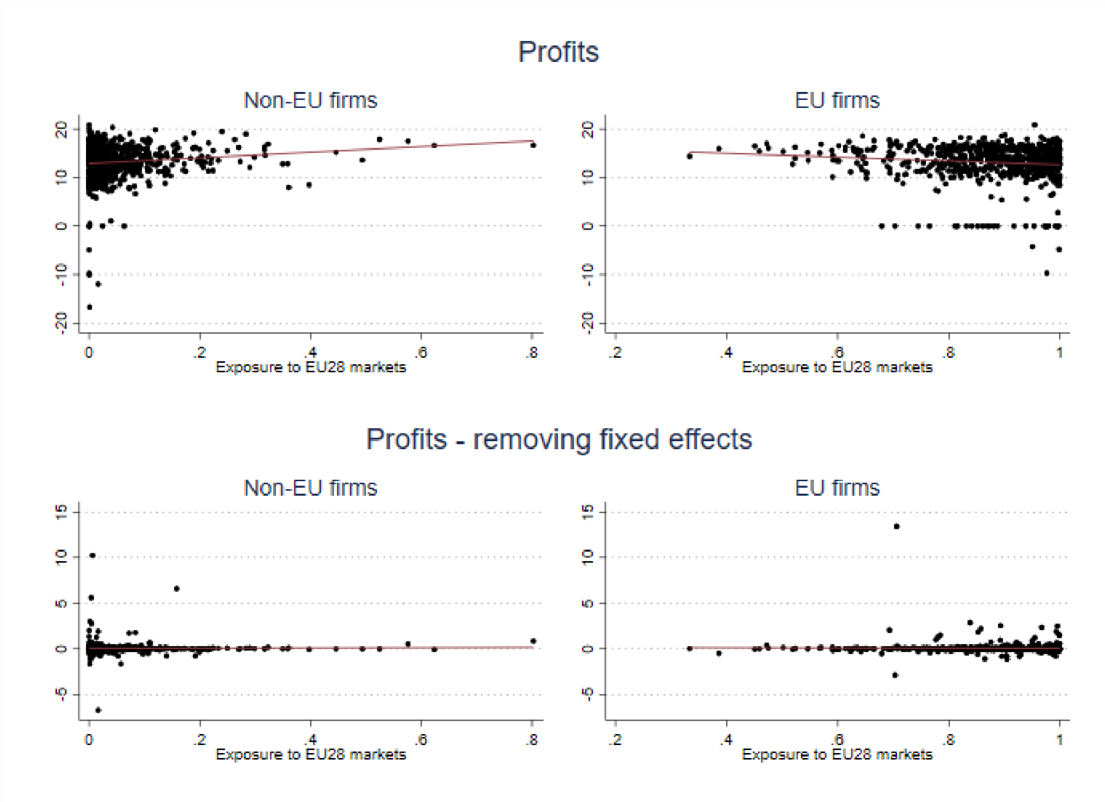
Table A4: Exposure to the GDPR and patent applications by IT services providers.

	(1) Patent applications
Exposure to GDPR	50.656*
	(30.392)
Exposure to GDPR $\times$ IT	39.581
	(61.180)
Exposure to GDPR $\times$ IT $\times$ small	-2.146
	(51.247)
Observations	308,436
R-squared	0.900
Plant FE	yes
Country x 1-dig-industry x year FE	yes

The table shows OLS estimates based on 4. The dependent variable is the number of patent applications. Exposure to the GDPR is the 2010 (base year) share of output sold to European countries in each country-2-digit industry pair, and interacted with a dummy taking value 1 from 2018 onward. IT firms are firms in industries NACE Rev. 2 J62 "Computer programming, consultancy and related activities" and J63 "Information service activities" from the OECD ICIO tables. Small firms have less than 500 employees in 2010 or in the first year of observation after 2010. Standard errors are clustered at the country-2-digit industry-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

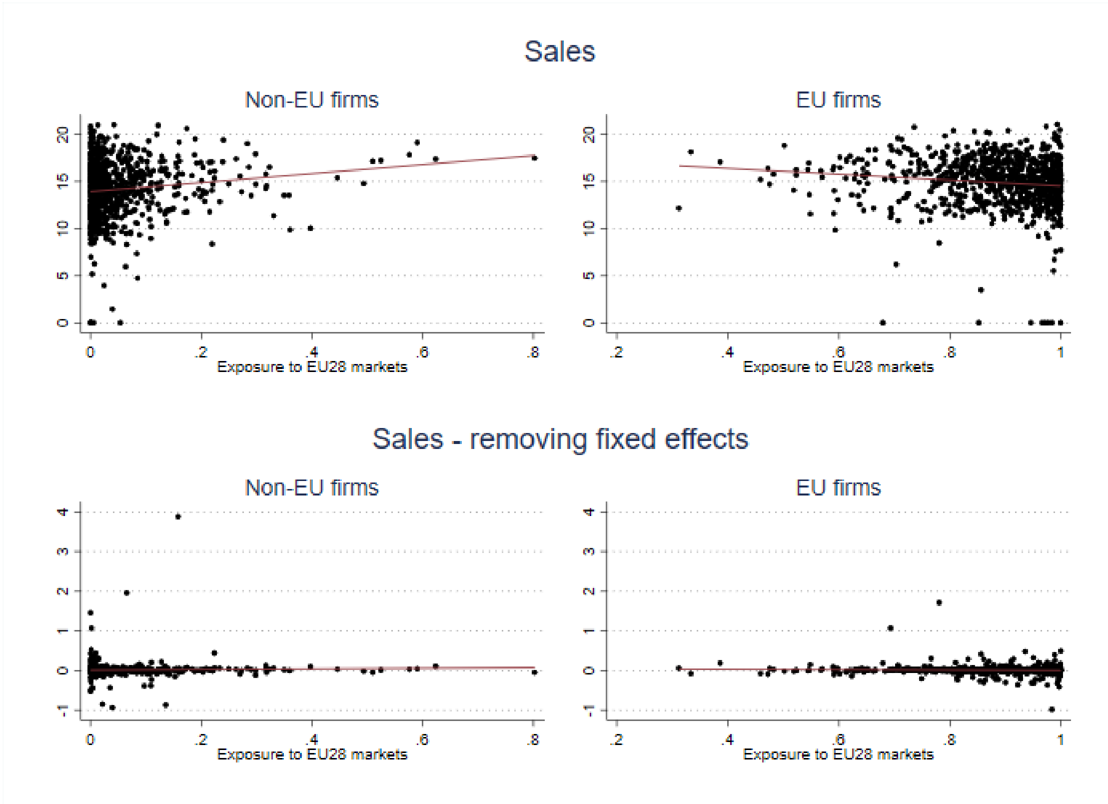
Online Appendix (not for publication)

Figure OA 1: Correlation between base year exposure to EU28 markets and firm-level profits.



The top panel of the figure presents the correlation between 2010 (base year) exposure to EU28 markets and firm-level log-profits. The bottom panel of the figure presents the correlation between 2010 (base year) exposure to EU28 markets and the residuals of a regression of log-profits on firm fixed effects. To improve the readability of the figure, the top and bottom panels present median values within country and 2-digit industry pairs.

Figure OA 2: Correlation between base year exposure to EU28 markets and firm-level sales.



The top panel of the figure presents the correlation between 2010 (base year) exposure to EU28 markets and firm-level log-profits. The bottom panel of the figure presents the correlation between 2010 (base year) exposure to EU28 markets and the residuals of a regression of log-sales on firm fixed effects. To improve the readability of the figure, the top and bottom panels present median values within country and 2-digit industry pairs.

Table OA 1: Exposure to the GDPR, firm-level profits and sales: placebo tests.

	(1) Profits	(2) Sales	(3) Profits	(4) Sales	(5) Profits	(6) Sales
Exposure to GDPR (2016)	-1.539***	-0.252				
	(0.473)	(0.180)				
Exposure to GDPR (2014)			-0.769	-0.516		
			(1.589)	(0.467)		
Exposure to GDPR (2012)					-0.246	-0.275
					(0.908)	(0.294)
Observations	1,332,456	1,332,456	1,332,456	1,332,456	1,332,456	1,332,456
R-squared	0.687	0.944	0.687	0.944	0.687	0.944
Firm FE	yes	yes	yes	yes	yes	yes
Country x 1-dig-industry x year FE	yes	yes	yes	yes	yes	yes

The table shows OLS estimates based on 2. The dependent variables are expressed in logs. Exposure to the GDPR is the 2010 (base year) share of output sold to European countries in each country-2-digit industry pair, and interacted with dummies taking value 1 from 2016, 2014 and 2012 onward, respectively. Standard errors are clustered at the country-2-digit industry-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table OA 2: Exposure to the GDPR, firm-level profits and sales: controlling for EU-specific industry trends.

	(1) Profits	(2) Sales
Exposure to GDPR	-1.156***	0.023
	(0.318)	(0.248)
Observations	1,331,082	1,331,082
R-squared	0.690	0.945
Firm FE	yes	yes
Country x 1-dig-industry x year FE	yes	yes
EU country x 4-dig-industry x year FE	yes	yes

The table shows OLS estimates based on 2. The dependent variables are expressed in logs. Exposure to the GDPR is the 2010 (base year) share of output sold to European countries in each country-2-digit industry pair, and interacted with a dummy taking value 1 from 2018 onward. Standard errors are clustered at the country-2-digit industry-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table OA 3: Exposure to the GDPR, firm-level profits and sales: EU demand shifters.

	(1) Profits	(2) Sales
Exposure to GDPR	-1.505***	-0.299
	(0.496)	(0.232)
EU demand shifters	-0.087	0.028
	(0.089)	(0.029)
Observations	1,273,418	1,273,418
R-squared	0.684	0.945
Firm FE	yes	yes
Country x 1-dig-industry x year FE	yes	yes

The table shows OLS estimates based on 2. The dependent variables are expressed in logs. Exposure to the GDPR is the 2010 (base year) share of output sold to European countries in each country-2-digit industry pair, and interacted with a dummy taking value 1 from 2018 onward. The EU demand shifter is the product of (non-EU) country-2-digit industry shares of output sold to European markets and the yearly log-change of real value added in the EU region. European firms are dropped from the sample prior to estimation. Standard errors are clustered at the country-2-digit industry-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table OA 4: Exposure to the GDPR, firm-level profits and sales: controlling for firm-level capital and labor.

	(1) Profits	(2) Sales
Exposure to GDPR	-0.934***	-0.087
	(0.338)	(0.095)
Log-capital	0.784***	0.875***
	(0.023)	(0.011)
Log-employment	0.073***	0.045***
	(0.027)	(0.013)
Observations	642,229	642,229
R-squared	0.791	0.988
Firm FE	yes	yes
Country x 1-dig-industry x year FE	yes	yes

The table shows OLS estimates based on 2. The dependent variables are expressed in logs. Exposure to the GDPR is the 2010 (base year) share of output sold to European countries in each country-2-digit industry pair, and interacted with a dummy taking value 1 from 2018 onward. Standard errors are clustered at the country-2-digit industry-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table OA 5: Exposure to the GDPR, firm-level profits and sales: samples with different country coverage.

	(1) Profits	(2) Sales	(3) Profits	(4) Sales	(5) Profits	(6) Sales	(7) Profits	(8) Sales	(9) Profits	(10) Sales
Exposure to GDPR	-0.972***	-0.316*	-0.918***	-0.378*	-1.239***	-0.352*	-1.493***	-0.303	-1.759*	-0.286
	(0.320)	(0.185)	(0.351)	(0.206)	(0.391)	(0.185)	(0.498)	(0.231)	(0.902)	(0.341)
Observations	707,663	707,663	650,799	650,799	1,303,926	1,303,926	1,273,418	1,273,418	681,657	681,657
R-squared	0.699	0.858	0.675	0.835	0.685	0.944	0.684	0.945	0.577	0.908
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country x 1-dig-industry x year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Countries excluded	China	China	non-OECD	non-OECD	US	US	EU28	EU28	OECD	OECD

The table shows OLS estimates based on 2. The dependent variables are expressed in logs. Exposure to the GDPR is the 2010 (base year) share of output sold to European countries in each country-2-digit industry pair, and interacted with a dummy taking value 1 from 2018 onward. Standard errors are clustered at the country-2-digit industry-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Figure OA 3: An example of technology related to the GDPR — “Data Consent Manager”

BACKGROUND

Data privacy is a concern for many individuals and organizations. Legislation has been brought in to many jurisdictions (GDPR in the EU for example) that gives rights to individuals to control access to their own data. Ignoring these new rules can result in adverse consequences for any persons or organizations found to be mishandling data. Mishandling data need not be done maliciously and can arise due to human error or lack of knowledge of the law.

Conversely, access to data (and “big data” in particular) is a powerful tool that can help in numerous technical fields, including medical research and machine learning. The larger a data set the more accurate findings can be, and so access to the data of thousands, or even millions, of individuals is a very powerful, and valuable, resource. Some of the most useful data, such as medical data, is understandably particularly well controlled, and held for millions of individuals by a single organization (such as the NHS in the UK for example). Analysis and correlation of data sets across populations can improve the identification of factors affecting heath issues. This reduces the time taken to develop treatments, potentially saving and improving lives.

Data privacy and control, and the need for an organization to demonstrate compliance with data privacy law is diametrically opposed to sharing personal data for the good of humanity overall.

Various aspects of the disclosure may therefore relate to improved access and control of access to data.

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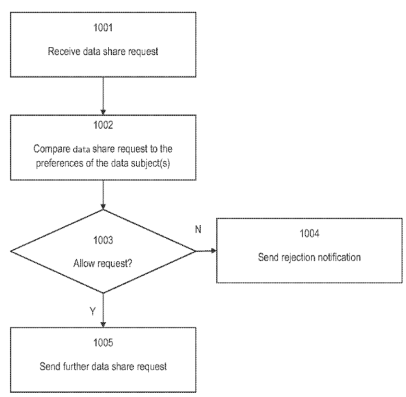
Title
[EN] DATA CONSENT MANAGER



Abstract
[EN]
A computer implemented method of managing consent for sharing data, the method comprising: storing data sharing preferences for a data subject in relation to data held by a plurality of data controllers; receiving a data share request from a requestor to obtain personal data relating to the data subject and held by one or more of the data controllers; comparing the data share request to the data sharing preferences of the data subject; and for each of the one or more data controllers: instructing the one or more data controllers to share the personal data with the requestor, or rejecting the data share request, in dependence on the comparison.

Related patent documents
EP3869371

The figure presents key information extracted from a patent document using PATENTSCOPE. Source: PATENTSCOPE

OB 1 Data Cleaning Procedure

- Keep unconsolidated account when possible: U1, U2, C1
- Keep end-of-the-year report
- Keep local registry, since annual reports are very few
- Keep observation starting in 2010 (our base year)
- Keep company-years with non-missing information on profits, sales and employment
- Drop the entire company (all years) if total assets is negative in any year
- Drop the entire company if employment (in persons) is negative in any year and companies with employment larger than that of Walmart (2 million) in any year
- Drop the entire company if sales are negative in any year.
- Drop the entire company if Tangible /intangible Fixed Assets (such as buildings, machinery, etc.) is negative in any year.
- Drop the entire company when reporting in any year a value of employment per million of total assets larger than the 99.9 percentile of the distribution.
- Drop the entire company when reporting in any year a value of employment per million of sales larger than the 99.9 percentile of the distribution.
- Drop the entire company when reporting in any year a value of sales to total assets larger than the 99.9 percentile of the distribution.