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ABSTRACT

By regulating how firms collect and use data, privacy laws may alter firm demand for information technology inputs. We study how firms respond to privacy laws in the context of the EU's General Data Protection Regulation (GDPR) by using seven years of data from a global cloud-computing provider. Our difference-in-difference estimates indicate that, in response to the GDPR, EU firms decreased data storage by 26% and data processing by 15% relative to comparable US firms, becoming less "data-intensive." To estimate the costs of the GDPR for firms, we propose and estimate a production function where firms combine data and computation in firm production. We find that data and computation are strong complements and that firm responses are consistent with the GDPR, representing a 22% increase in the cost of data. This increase translates into only a 0.1–0.6% rise in overall production costs because data plays a relatively small role in firm production compared to computation.

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A data appendix is available at http://www.nber.org/data-appendix/w32146

1 Introduction

In the information age, the production of goods and services increasingly relies on the processing of data (Agrawal et al., 2018; Goldfarb and Tucker, 2019). Since some of the most valuable data concerns personal information, its growing use has led to new policy attention and regulation. One of the most influential privacy laws is the European General Data Protection Regulation (GDPR), which was enacted in 2016 and affects more than 20 million firms across dozens of countries (GDPR.eu, 2019; Johnson, 2022). Many countries have since followed this example: as of early 2022, 157 countries had enacted legislation to secure data and privacy (Greenleaf, 2022).

While these privacy laws help harmonize and improve data collection practices, they can also be costly for firms (Peukert et al., 2022; Johnson et al., 2023; Aridor et al., 2023; Goldberg et al., 2023). For example, privacy regulations may generate a wedge between the marginal product of data and its marginal cost, leading firms to substitute data with other inputs. Variations in these wedges across firms can result in misallocation of inputs in the economy (Hsieh and Klenow, 2009). Given the increasing role of data in firm production, understanding the cost of privacy regulations and how they affect firms' input decisions is of utmost importance.

However, large-scale empirical evidence of how privacy laws affect firm data decisions is scant. Studying this question is complicated for a number of reasons (Johnson, 2022). First, firms' data and computation usage are inherently difficult to observe, as standard firm datasets do not provide information on these measures. Second, there is no unified framework for analyzing the role of data in firm production (Veldkamp and Chung, 2023). Any such framework needs to be parsimonious while having enough flexibility to allow the effect of privacy laws to depend on the importance of data and computation for firms.

In this paper, we make progress on these fronts by studying how the GDPR affected firms' input choices by proposing a production framework with data and computation and using a dataset from a large global cloud-computing provider. The cloud is an ideal setting for this study because it enables us to observe firms' high-frequency data and computation usage across tens of thousands of firms over a seven-year period from 2015 to 2021. This data spans most major industries, from manufacturing to services, allowing us to analyze the effect of privacy regulations beyond the digital economy.

In our initial set of analyses, we apply this data toward studying the direct effect of the GDPR on firm data and computation choices. We compare domestic firms in the European Union (EU) subject to the GDPR to similar, non-treated domestic firms from the same industry in the US using a difference-in-differences approach. Building on these

empirical findings, our main analysis develops a production function model with data and computation. Using this model, we estimate how firms combine data and computation in production and quantify the wedges generated by the GDPR along with the corresponding increase in production costs.

We begin by summarizing the key features of the GDPR. The GDPR is a landmark privacy law enacted in 2016 and implemented in 2018. Its regulations apply to all firms in the EU, as well as non-EU firms offering goods or services to "data subjects" within the EU. This law increased the cost of collecting and storing data for firms by requiring enhanced data protection, increasing penalties in case of data breaches, and giving consumers data-rights requests such as data correction and deletion. Survey evidence suggests that GDPR compliance is costly, ranging from $1.7 million for small to medium-sized businesses to $70 million for large ones (Accenture, 2018; Hughes and Saverice-Rohan, 2018).

Next, we discuss the specific context in which we observe firm data decisions: the cloud. Cloud computing is a widely adopted information technology (IT) that enables firms to store and process data remotely over the internet (Byrne et al., 2018; Brand et al., 2025). Using data from our cloud computing provider, we observe firm-level monthly usage of "storage"—the amount of data stored in gigabytes—and "compute"—the number of core-hours of computation. We also observe other information, such as prices and the locations of the data centers where firms do computation and store their data. We match our cloud usage data to other data sources that provide information on firm characteristics.

Our first set of results comes from an event study design comparing data and computation use among comparable domestic firms in the EU and the US after the GDPR. While our focus on the domestic firms excludes multinational firms, it allows us to define clean treatment and control groups. We find that EU firms stored on average 25.7% less data than US firms two years after the GDPR. The direction of this relative decline in data is perhaps unsurprising, given that the GDPR primarily regulates data usage, but the magnitude is noteworthy. We also find that EU firms reduced their computation relative to US firms by 15.4%—implying that firms became less data-intensive after the GDPR.[1] Our heterogeneity analysis suggests that these patterns are present across all industries we study (software, services, and manufacturing), with differences in magnitude across industries.

While our event study findings provide direct evidence of the GDPR's impact on firms' data and computation inputs, they offer a limited understanding of the associated economic costs of the regulation. Since data are inputs in firm production, recovering the

[1]It is ex-ante unclear how the GDPR would affect computation; this effect theoretically depends on the substitutability between data and computation (Acemoglu, 2002).

regulatory wedges from firms' input choices and, ultimately, the effect of regulation on firms' overall production costs depends on how firms use data in production.

Motivated by this, we propose a production function model where firms aggregate data and computation through a constant elasticity of substitution (CES) function. This aggregation function, which we call "information production," includes two key parameters: (i) *the firm-specific compute-augmenting productivity*, which determines relative factor intensity of computation and data (Doraszelski and Jaumandreu, 2018; Raval, 2019; Demirer, 2025), and (ii) *the elasticity of substitution between computation and data*, which governs how firms adjust these inputs in response to changes in factor prices (Hicks, 1932). Our model accommodates many of the uses of data proposed in the literature (Jones and Tonetti, 2020; Farboodi and Veldkamp, 2026) and emphasizes the role of computation in firm production.

Our production function model provides an input demand function that links firms' cost-minimizing data and computation choices to input prices and model parameters. Using a shift-share design to instrument input prices, we estimate this input demand function for each industry to recover the parameters of the production function. We find that data and computation are strong complements in production, with elasticity of substitution ranging from 0.32 (manufacturing) to 0.44 (software). This complementarity suggests that firms cannot easily substitute toward computation when faced with increased data costs. To our knowledge, this is the first estimate of a production function with data inputs, which contributes to our understanding of production functions in modern firms.

To recover the distortion generated by the GDPR, we model it as a wedge between the variable cost of storing data in the cloud and the total variable cost that includes GDPR compliance costs. This wedge arises from various sources of regulatory costs, including penalties in case of breaches, higher data security requirements, and the need for detailed data records. We estimate firm-specific wedges by attributing them to the changes in post-GDPR input choices unexplained by changes in input prices or changes in the elasticity of substitution.

Our estimates suggest that the GDPR increased the variable cost of data inputs by 22.4% for firms on average. Firms in data-intensive industries faced higher costs, with the largest effect observed in the software sector (28.1%), followed by services (20.3%) and manufacturing (15.3%). What determines the increase in costs? To provide suggestive evidence, we analyze the relationship between firm-specific wedges and two firm characteristics: (i) firm size, measured by the number of employees, and (ii) compute-augmenting productivity, estimated from the production function. We find that larger and more compute-intensive firms experienced smaller cost increases from the GDPR.

In the final part of the paper, we use our production function estimates to quantify how

the 22.4% GDPR-induced increase in the cost of data translates into firms' total variable production costs. Our analysis proceeds in two steps. First, we analyze its impact on the cost of aggregating data and computation in information production, and then examine how changes in information costs affect total production costs.

We find that although the average firm-level wedge is quite large (22.4%), the resulting increases in the variable cost of producing information are quite low (3.9%), primarily because data's cost share in information production is considerably smaller than that of computation (23.0% vs. 77.0%). In other words, although strong complementarity limits firms' ability to substitute data for computation when data becomes more costly, the expenditure share of the data is small to begin with, limiting the GDPR's impact on the cost of information.

Next, to estimate the effect of the GDPR on the total production cost, we perform a simple back-of-the-envelope calculation, assuming a CES technology in information and non-information inputs (e.g., capital, labor). We calibrate this model using estimates from Lashkari et al. (2024) and other data sources. We find that the GDPR increases variable production costs by 0.62% for software firms, with smaller effects in services (0.16%) and manufacturing (0.08%) industries. When aggregated across all EU firms in the industries we analyze, this corresponds to an annual increase in production costs of €18.1 billion.

We conduct additional analyses to show that our results are robust to many concerns. First, we show that our results are similar when we exclude multi-cloud firms, suggesting that results are not driven by EU firms substituting toward other cloud providers. Second, we find similar results when estimating our empirical strategy using only start-ups, which tend to use cloud computing as their only IT—suggesting that substitution to on-premises IT (hybrid cloud) is not a large concern. Third, we show that our results are not driven by differential trends in cloud prices in the EU and the US. Finally, we estimate our specification while excluding firms using web services, showing that the results do not only come from websites, which experienced cookie consent changes under the GDPR.

Nevertheless, we acknowledge some relevant limitations of our study. Unlike many previous GDPR studies, our paper is based on a large sample of firms. While this allows us to draw more generalizable conclusions about firms' data uses, the trade-off is that we observe less detailed information than an in-depth single-firm study. For example, although we observe detailed measures of the quantity of data and computation used by firms, we cannot be as precise about the role of data for the firm as more focused studies can be. Moreover, our analysis excludes multinational enterprises, which are often larger, more productive, and may be important for understanding how data regulations affect firm production and productivity growth (Bloom et al., 2012). Finally, we emphasize that

our results focus on the variable production costs imposed by the GDPR and do not capture other potential costs—such as effects on innovation or aggregate misallocation (Jia et al., 2021)—nor do they address the benefits of privacy regulation (Arrieta-Ibarra et al., 2018).[2]

Contribution to the Literature The first body of literature we contribute to is the research on the impact of the GDPR on firms (Johnson, 2022). This literature finds that the GDPR decreased the investment in technology ventures, encouraged app exit, and discouraged app development (Kircher and Foerderer, 2020; Jia et al., 2021; Janßen et al., 2021). Several papers document adverse impacts on digital tracking and advertising: the GDPR decreased the usage of tracking technology tools (Lefrere et al., 2025; Aridor et al., 2023; Miller et al., 2025), decreased page views and e-commerce revenue (Goldberg et al., 2023), decreased the number of website visits (Schmitt et al., 2022), increased market concentration in the advertising sector (Peukert et al., 2022; Johnson et al., 2023), and increased search frictions (Zhao et al., 2021). On the benefits side, Aridor et al. (2023) find an increase in the average value of data for advertising, while Godinho de Matos and Adjerid (2022) document improvements in targeting effectiveness due to the GDPR. Although most evidence suggests that the GDPR has impacted data-driven economic activity, Zhuo et al. (2021) find a null short-term effect on the formation and termination of internet infrastructures between GDPR and non-GDPR countries.[3]

While our paper builds on an identification strategy similar to some of these GDPR papers, it differs in two aspects. First, because of the unique feature of our data, we go beyond digital outcomes to analyze firms' data and computation decisions, margins directly targeted by the regulation. By studying these outcomes, we also complement the literature that focuses on accounting and aggregate measures of firm performance, such as profit and sales (Koski and Valmari, 2020; Frey and Presidente, 2024). Second, we take a production function approach. This approach allows us to structurally estimate the role of data and computation in production and to calculate the cost of the GDPR for firms.

Second, our study relates to the production function literature by estimating a production function with data inputs (Olley and Pakes, 1996; Ackerberg et al., 2015). A recent theoretical literature has proposed different ways of how firms use data, with Jones and Tonetti (2020) modeling data as a non-rival input generated as a byproduct of production and Farboodi and Veldkamp (2026) modeling data as a productivity-enhancing input through better prediction. On the empirical side, some studies have included IT in firm production by using various IT expenditures, such as software and hardware, as inputs (Brynjolfsson and Hitt, 2003; Lashkari et al., 2024). We contribute to this literature by

[2]Quantifying the privacy benefits is known to be difficult (Acquisti et al., 2016; Lin and Strulov-Shlain, 2023).
[3]A recent literature has studied the California Consumer Privacy Act (Canayaz et al., 2022; Doerr et al., 2023).

estimating a micro-level production function that incorporates physical measures of two fundamental modern IT inputs: data and computation.

Third, our paper is related to the misallocation literature, which studies inefficiencies in factor allocations resulting from various frictions (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). We employ a similar empirical strategy by modeling distortions as wedges between the marginal revenue product of an input and its price. Although this literature often abstracts from the origins of frictions, some recent papers have focused on their sources, such as labor market institutions (Bertrand et al., 2025), market power (Asker et al., 2019; Peters, 2020), and monopsony power (Berger et al., 2022). We contribute to this literature by studying the input distortions introduced by a landmark global regulation.

Our paper also contributes to the economics of privacy literature by evaluating the effects of the largest privacy regulation on firms (Goldfarb and Tucker, 2011, 2012; Acquisti et al., 2016; Athey et al., 2017; Choi et al., 2019; Montes et al., 2019; Ichihashi, 2020; Loertscher and Marx, 2020; Chen et al., 2021; Krähmer and Strausz, 2023).

2 Institutional Setting

This section first discusses the relevant details of the GDPR. We then describe cloud computing technology, the setting for our primary data source in this paper.

2.1 The European General Data Protection Regulation

There is perhaps no policy more important in the modern privacy landscape than the GDPR. As Johnson (2022) notes, "In many ways, the GDPR set the privacy regulation agenda globally." As such, understanding the consequences of the GDPR is vital not only because of its impacts on firms but also because of its crucial role in shaping privacy laws. In this section, we describe the key features of this policy and its implications for firms.

The GDPR is a set of rules that govern the collection, use, and storage of personal data belonging to individuals within the EU. It was enacted in April 2016 and came into force in May 2018. By consolidating and enhancing existing privacy provisions, the GDPR introduced a harmonized approach to privacy regulations across the EU.[4] We provide a detailed description of the changes required for firms after the GDPR in Appendix B.1 and summarize its most important characteristics below.

The GDPR applies whenever the firm that controls the data ("data controller") is established in the EU or whenever the individuals ("data subjects") whose data is collected

[4]Unlike the GDPR, which is directly binding across the EU, the preceding Directive 95/46/EC had to be incorporated into each member state's national laws, leading to variation in its implementation across states.

are located in the EU, regardless of their citizenship or residence (Article 3). It broadly defines personal data as any information relating to an identified or identifiable natural person (Article 4). This includes information such as name, address, email address, and internet protocol (IP) address. It applies to *all* personnel data both in the client and employee context, making even business-to-business firms subject to compliance.

Two aspects of the GDPR are particularly important for our paper. First, the GDPR takes a data protection approach rather than a consumer protection approach as in the US (Boyne, 2018; Jones and Kaminski, 2020). A data protection approach imposes a set of costly responsibilities on firms to protect data, in addition to a substantive system of individual rights. Second, the GDPR takes a risk-based approach to data protection without clarity on the specific measures firms must take, making implementation firm-dependent (Hustinx, 2013; Gellert, 2018). For example, Article 25 (Data Protection by Design and by Default) uses phrases such as "taking into account the state of the art, the cost of implementation [. . .] as well as the risks" and requires that controllers "implement appropriate technical and organizational measures [. . .] in an effective manner." This risk-based approach makes regulatory costs heterogeneous across firms.

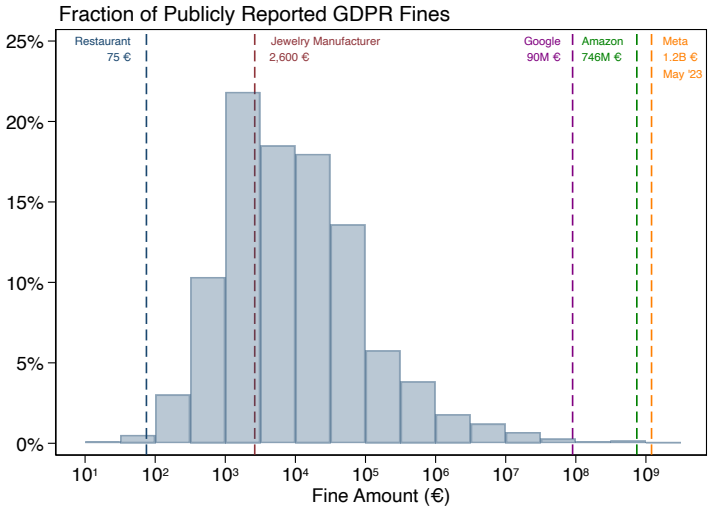
From the firm perspective, the GDPR mainly increased the cost of collecting and storing data by imposing costly responsibilities on firms. These include designating a data protection officer (Article 37), preparing data protection impact assessments (Article 35), implementing appropriate technical and organizational measures for data security (Article 32), keeping a record of processing activities (Article 30), providing timely notifications in case of data breaches (Article 33), fulfilling consumers' requests for data transfer, erasure, or rectification (Articles 14-21), and paying penalties in case of data breaches (Article 83).[5]

The cost of complying with the GDPR can vary depending on the size and complexity of an organization. There are no official statistics, but most survey evidence suggests that complying with the GDPR is costly. The estimates range from an average of $3 million (Hughes and Saverice-Rohan, 2018) and $5.5 million (Ponemon Institute, 2017) to $13.2 million (Ponemon Institute, 2019) and $70 million for the largest firms (Accenture, 2018), depending on the composition of surveyed firms. The survey evidence indicates that a large percentage of the costs (between one-fifth and one-half) are labor costs, followed by technology, outside consulting, and internal training (Ponemon Institute, 2019; Hughes and Saverice-Rohan, 2019).

The changes mandated by the GDPR entail both fixed and variable costs. For example,

[5]Firms also must have a legal basis for processing personal data. Contrary to popular belief, consent is not the only appropriate legal basis—contractual necessity, legal obligation, vital interests, public task, and legitimate business interest may also serve as a basis for processing data (Article 6).

Figure 1: Distribution of Publicly Reported GDPR Fines



Notes: The figure presents the distribution of 1,730 publicly available GDPR fines, noting that not all GDPR fines are made public. Appendix B.3 describes the data collection process. Fines are presented in nominal terms (€), and five examples from the data have been highlighted.

the cost of having a data protection officer may not scale with data size, so it could be considered a fixed cost. On the other hand, the costs of handling customers' access requests, the liability in case of a data breach, and keeping data secure would increase with data and firm size.[6] As such, it may be more sensible to interpret these kinds of costs as marginal costs. We provide a detailed classification of GDPR costs into these fixed and variable cost categories and present corresponding survey evidence in Appendix B.2.

In addition to these direct costs, firms may also incur indirect costs such as cybersecurity insurance premiums or penalties if they are found to be non-compliant. Non-compliant firms may face fines of up to 4% of their organization's annual *global* revenue or €20 million (whichever is greater). We scraped publicly available GDPR fine data from a database maintained by CMS, an international law firm.[7] In Figure 1, we provide the size distribution of these GDPR fines.[8] We note two key features of these fines. First, enforcement is not limited to large violations: 25% of the fines have been under €2,000 levied on small businesses. Second, the GDPR applies to a much broader set of businesses and industries than just software and technology firms. Figure 1 highlights some of these cases, which include fines on restaurants and manufacturers.

[6]There are likely additional costs beyond the direct financial costs of compliance, including opportunity costs of diverting existing employees towards GDPR compliance and disruption caused by operational changes.
[7]See `https://www.enforcementtracker.com`. Appendix B.3 describes this dataset.
[8]The total cumulative fines imposed in this dataset have amounted to over €3 billion, with 1,730 being fined. This figure is likely to be an underestimate because not all GDPR fines are made publicly available.

2.2 Our Setting: Cloud Technology

Cloud computing provides scalable IT resources on demand over the internet. According to the National Institute of Standards and Technology (Mell et al., 2011), cloud computing is defined as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released." Cloud computing has experienced rapid growth since its introduction, with nearly 80% of firms using at least one cloud function as of 2018 (Zolas et al., 2021).[9]

We focus on the two primary cloud services: storage and computation. Storage services allow users to store data in a data center. Computation services allow users to run applications and perform computations in a virtual machine (VM). Firms may use storage and computing services in multiple parts of their production, including powering digital services, optimizing logistics, supporting product development, and handling administrative tasks such as human resources and accounting. Firms may also use storage without computing services, such as a newspaper hosting website photographs in the cloud and using them directly without computing. However, it is rare to observe firms using computation without storage, although non-data simulations might serve as an exception.[10]

From the researchers' point of view, the cloud's existence and ubiquity provide important advantages over traditional IT. Because cloud computing is typically provided by large third-party firms, it is possible to aggregate data from tens of thousands of firms. Moreover, cloud providers keep detailed records of their users' activity for billing purposes, allowing usage to be tracked consistently over time.

Despite these advantages, there are limitations to using data from cloud computing. First, many firms use a mix of cloud computing and on-premises IT, especially during the transition to the cloud. In such cases, we can only observe firms' data in the cloud and not from their on-site hardware, which may bias our results if the GDPR changes the composition of cloud and on-site data. Second, firms frequently use cloud services from multiple providers, known as multi-cloud (Accenture, 2022). For these firms, a decline in cloud usage from one provider could come from substitution to another provider. We take these concerns seriously and provide several robustness checks in our empirical strategy.

[9] See Jin and McElheran (2017); Jin (2022); DeStefano et al. (2023) for recent studies on firms' cloud adoption and the effects of cloud technology on firms.

[10] See several case studies of how firms in different industries use cloud computing at AWS Case Studies, Azure Customer Stories, and Google Cloud Customers. All web links provided in the footnotes were accessed on February 3, 2026.

3 Data and Summary Statistics

This section describes the main datasets used in the paper and presents basic summary statistics. We leave the exact data construction details to Appendix C.

3.1 Cloud Computing Data (2015-2021)

We obtain information through one of the largest cloud technology providers. Using these data, we observe storage and computation usage for the universe of our provider's customers between 2015 and 2021. For each service, we observe the number of units purchased, the location of the data center, the date, and the price paid. Therefore, we have both the physical unit of usage and expenditures.

We measure storage in gigabytes and computing in core-hours (number of cores $\times$ number of hours). Core-hours are a commonly used metric to quantify computational work in cloud computing.[11] We use this data to construct monthly usage at the firm-location (data center) level for storage and computation. As a result, we can observe data stored in the US and EU separately by the same firm. Through this data, we also observe SIC industry codes, headquarters location, and whether a firm is a startup or not.[12] Additional details on this data are provided in Appendix C.1.

One limitation of our dataset is that it does not allow us to see which specific data firms are collecting, nor the exact ways in which they use the data. This limits our ability to speak to some important questions about how firms specifically use data.

3.2 Cloud Computing Usage from Other Providers (2016-2021)

To address the concern of observing data from a single provider, we use an establishment-level IT data panel produced by a market research company called Aberdeen (previously known as "Harte Hanks"). Aberdeen compiles data on cloud technology adoption (including provider) using web crawling, surveys, and publicly available sources. This dataset covers around 3.8 million companies worldwide between 2016 and 2021 at the yearly level. Previous versions of this data have been widely used by researchers to construct measures of IT usage.[13] We match our cloud computing data to Aberdeen firms using a matching procedure described in Appendix C.3 based on name, location, domain, and other infor-

[11] To illustrate the concept, consider the example of a software engineer in a startup who runs a VM with eight cores for five hours. In this case, the usage is recorded as 40 compute units.

[12] The "start-up" classification is defined internally by the cloud technology provider.

[13] See e.g., Bloom et al. (2012). Note that Aberdeen's data has undergone changes in recent years, relying more on web scraping and extrapolation than on surveys. We conduct cross-checks against our internal data to assess the accuracy of Aberdeen's estimates of cloud adoption. See Appendix C.3 for more details.

Table 1: GDPR Applicability Matrix by Location from Peukert et al. (2022)

		Firm Location	
		EU	US
Location of Consumer / Employee Data Used	EU	**Case 1** GDPR applies *Art. 3(1) GDPR*	**Case 3** GDPR applies *Art. 3(2) GDPR*
	US	**Case 2** GDPR applies *Art. 3(1) GDPR*	**Case 4** GDPR does not apply –

Notes: Table is taken from Table 1 of Peukert et al. (2022). The matrix shows whether the GDPR is applicable to firms located within and outside the EU.

mation, achieving a match rate of 62.7%. We use Aberdeen data to identify single-cloud firms and examine differential changes in cloud providers' market shares in the EU and the US around the GDPR.

3.3 Other Datasets: Firm Characteristics

We augment our data with employment information by merging it with the European Orbis database from Bureau van Dijk via name- and domain-based matching. With this procedure, we link cross-sectional employment data to approximately 69.6% of the European firms. For firms matched to Orbis, employment is taken from Orbis and otherwise from Aberdeen, which sources it from Dun & Bradstreet. We use the employment information in 2018 to define firm size in our heterogeneity analysis.[14]

3.4 Sample Construction and Summary Statistics

We begin by presenting a framework that will allow us to classify firms by their exposure to the GDPR. Following Section 2, Table 1 presents information on whether the GDPR applies to firms depending on the location of the firm and data subjects (using the language from Peukert et al., 2022). Now, while we cannot directly observe the locations of each firm's employees and consumers, we use the fact that we can observe firm server locations to approximate the locations of their consumers and employees. We view this as a reasonable approximation because firms tend to choose data centers close to them to reduce latency

[14]While there are known concerns regarding employment imputations in Dun & Bradstreet (see, e.g., Crane and Decker, 2020), these concerns are attenuated in our setting because our analysis relies on employment quintiles rather than raw employment levels. For more information, see Section 6.2. Moreover, in Figure OA-6 of the Online Appendix, we report the relationship between employment quintiles in Orbis and Aberdeen for firms that appear in both datasets. We find that employment measures in Orbis and Aberdeen are highly correlated, with a correlation coefficient of 0.86.

(Fang and Greenstein, 2025). We argue that firms based solely in one geographic region are unlikely to use servers across the Atlantic unless they have consumers or employees located in the other location.[15]

By using information on the locations of firm server choices before the GDPR, we attempt to categorize firms into the four cases described in Table 1. We consider a firm multinational (Cases 2 and 3) if they use data centers both in Europe and in the US. We consider a firm to be a domestic EU or US firm (Cases 1 and 4) if they use data centers only in Europe or in the US.[16] As we explain later in more detail, our empirical strategy focuses on comparing domestic EU and US firms, and therefore, these domestic firms constitute our main sample throughout the paper.

As we discuss in Appendix C.2, we restrict our attention to firms that continuously used our cloud provider's services for the full year beginning two years prior to the introduction of the GDPR. This sample accounts for 90% of storage and computation. We use this sample restriction to focus our analysis on relatively stable users of cloud computing. Our sample is, therefore, comprised of firms that are both responsible for the vast majority of storage and computation in the pre-GDPR period and that have been continuously attached to our cloud computing provider.

Table 2 presents summary statistics for our baseline sample of nearly forty thousand firms. We categorize each firm's industry by using the firm's SIC code, and we intentionally split software firms from other firms in the services division due to their large share in our sample.[17] Therefore, throughout the paper, we use "services" to describe firms in the service industry excluding software firms, and "software" to describe firms in the software industry. The majority of firms belong to the services (42.6%) and software (25.4%) industries, but firms from manufacturing and various other industries are also represented in our sample. As reported in Columns (4-5), while there is variation in usage across industries—likely driven in part by the difference in the average size of firms using cloud computing—we observe significant storage and computation in all industries. We also note some slight variation in the share of firms in the US versus the EU by industry in Column (7), although each region always accounts for at least 40% of firms in each industry.

Lastly, Column (6) of Table 2 presents the mean data intensity for each industry, which

[15]One piece of evidence that supports server location choice being predictive of firm location is that when we construct EU vs US firms classifications using only server locations, the assigned regions coincide with the headquarter locations in our data for 98% of the firms.

[16]We also include UK firms in our EU sample. The UK was part of the EU when the GDPR came into effect on May 25, 2018. After the UK's withdrawal from the EU, the GDPR was incorporated into UK law as the UK GDPR, which largely mirrors the provisions of the GDPR, with some minor changes.

[17]We define software firms as those with SIC codes between 7370 and 7377.

Table 2: Summary Statistics

Industry	(1) Number of Firms	(2) Share Compute (%)	(3) Share Storage (%)	(4) Mean Storage	(5) Mean Compute	(6) Mean Data Intensity	(7) Share EU (%)
Services	15,886	36.3	31.9	844	628	1.84	40.9
Software	9,480	17.6	20.8	690	670	1.69	59.8
Manufacturing	3,095	10.5	11.6	1,293	986	1.81	54.4
Retail Trade	2,152	5.2	5.4	1,101	917	2.02	46.9
Finance & Insurance	2,057	11.4	10.8	1,652	1,571	1.89	44.9
Wholesale Trade	1,945	3.7	4.5	925	885	2.10	52.3
Other	2,689	15.3	15.0	1,714	1,616	2.23	46.1
All	37,304	100.0	100.0	1,000	803	1.86	48.1

Notes: Table presents summary statistics from our matched sample of firms. A description of the sample's construction can be found in Section 3.1, and a more detailed description of the sample construction can be found in Appendix C. Industries are defined as the ten divisions classified by SIC codes, with the exception of software firms, which are carved out of the services division and represent SIC codes 7370 - 7377. For confidentiality purposes, mean storage and compute have both been normalized such that mean storage is denoted by 1,000 units. We calculate mean data intensity at the firm level while restricting to firms that use both storage and computing services.

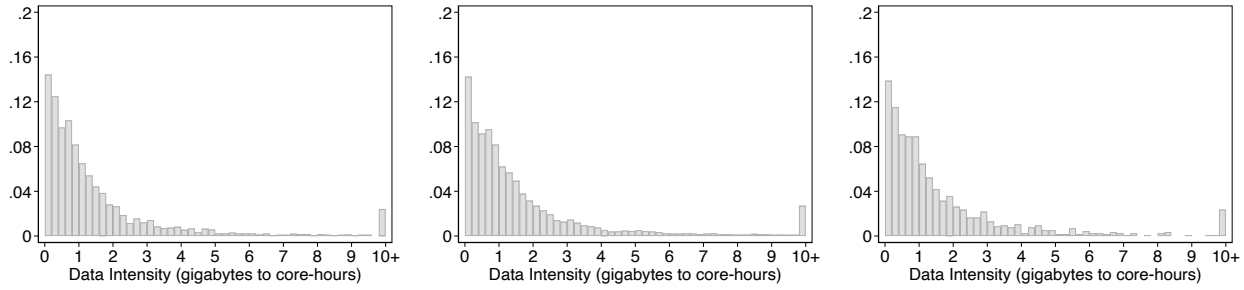
is defined as the ratio of storage to computation. We find that the average data intensity ranges from 1.69 to 2.23. However, these averages mask significant within-industry heterogeneity, as shown in Figure 2, which plots the distribution of data intensity for the three largest industries in our sample. The large firm-level variation in data intensity suggests that the roles of data and computation likely vary across firms.[18] This result is consistent with the large evidence of within-industry heterogeneity in other firm outcomes, such as productivity (Syverson, 2011), labor shares (Kehrig and Vincent, 2021), and markups (Autor et al., 2020; De Loecker et al., 2020). As we will see in Section 5, taking into account this heterogeneity will be important when developing a production function framework with data and computation.

4 Event Study Evidence

In this section, we apply an event study design to study the effect of the GDPR on firms' data and computation decisions. We begin by defining our empirical strategy and providing intuition for our identifying assumptions. Next, we present our baseline estimates and discuss the robustness of our strategy across various alternative samples and specifications.

[18]This result remains even if we focus on more narrowly defined 4-digit SIC industries.

Figure 2: Histogram of Data Intensity by Industry



(a) Software Firms **(b)** Services Firms **(c)** Manufacturing Firms

Notes: Figure presents a histogram of data intensity at the firm level, defined as the ratio of data stored to computation (the ratio of gigabytes to core hours) for each industry. Industries are defined through SIC codes (with the exception of software firms, which are carved out of the services division). We limit the sample to firms that have ever used both storage and computation ($N = 11,858$).

4.1 Empirical Strategy

Our empirical strategy aims to identify the causal effect of the GDPR on firms' data and computation choices. In order to identify a relevant treatment and control group for our strategy, we turn to our classifications of firm locations from Section 3. Following Table 1, we define "Case 1" as our treatment group and "Case 4" as our control group.

Notably, these two definitions exclude multinational firms (i.e., those with branches and/or consumers across countries). We choose to do so for two reasons. First, we may think of multinational firms as being partially treated: only some of their data may be subject to the GDPR. Thus, we might want to separate the estimation of the treatment effects of these firms from the fully treated firms (Case 1). Second, multinational firms may systematically differ from the control firms that we define (Case 4). They may respond to the GDPR along different margins than our control group, choosing to shift data, computation, and even business operations into or out of the EU.

Although restricting the sample to domestic firms allows us to cleanly separate firms subject to the GDPR and those that are not, it also introduces an important limitation: we cannot use this sample to study cross-country data reallocation by multinational firms or their entry into additional geographic markets. Our inability to speak to these additional margins could lead us to understate the overall effects of the GDPR. Accordingly, our estimates should be interpreted as a local average treatment effect (LATE), capturing the impact of the GDPR on domestic firms.

We focus on three outcomes: data, computation, and "data intensity" (the ratio of data to computation). Our empirical specification uses a difference-in-differences design and

estimates the following regression:

$$\log(Y_{it}) = \sum_{q \neq -1} \beta_q \cdot \mathbb{1}_{\{q\}} \cdot \mathbb{1}_{\{\text{EU}_i\}} + \alpha_i + \tau_{kqs} + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the outcome of interest for firm i, in month t. We use q to denote quarter, k to denote industry, and s to denote pre-GDPR cloud usage decile. In this specification, α_i is a firm-level fixed effect while τ_{kqs} are industry-by-quarter-by-usage-decile fixed effects, which allow for time trends to differ flexibly across industry-usage decile combinations.[19] We define eleven industries using the ten mutually exclusive and exhaustive divisions defined by one-digit SIC codes and carving out software from services.

We estimate this specification for the sample period from July 2015 to March 2020.[20] The coefficients of interest, β_q, represent the difference in outcomes relative to the quarter before the GDPR came into force. The identifying assumption of our empirical strategy is conditional parallel trends. As described above, we take advantage of our large sample and allow time trends in our outcomes to vary flexibly by industry and initial cloud usage levels in our baseline specification, with 110 distinct bins for each quarter (11 defined industries × ten pre-GDPR cloud usage deciles).

To discuss the short- and long-run estimates of the effect of the GDPR, we also present results in a table format using an alternative regression specification given by:

$$\log(Y_{it}) = \delta_1 \cdot \mathbb{1}_{\{\text{EU}_i\}} \cdot \mathbb{1}_{\{t \in \text{Jun/18-May/19}\}} + \delta_2 \cdot \mathbb{1}_{\{\text{EU}_i\}} \cdot \mathbb{1}_{\{t \in \text{Jun/19-Mar/20}\}} + \alpha_i + \tau_{kqs} + \varepsilon_{it}, \tag{2}$$

where the notation of α_i and τ_{kqs} is the same as in Equation (1). Our estimates are relative to the excluded group, which is the pre-GDPR period. Thus, the short-run coefficient (δ_1) and long-run coefficient (δ_2) estimate the average difference in the change of Y_{it} between treated and untreated firms in the first and second year after the GDPR came into force.

4.2 Results

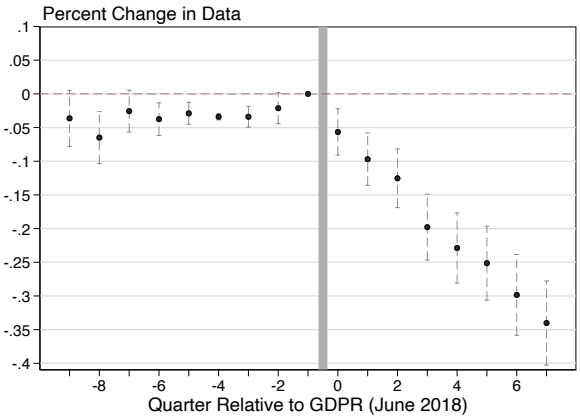
Our main event study results are shown in Figure 3, which plots the estimated coefficients β_q from Equation (1) for three outcomes. We discuss each of these outcomes separately and present the corresponding short- and long-run estimates from Equation (2) in Table 3.

[19] We measure cloud usage deciles for storage and computation outcomes by using a firm's storage or computation, respectively, as measured one year before the GDPR. For data intensity, we use terciles of firm storage interacted with terciles of firm computation to increase power.

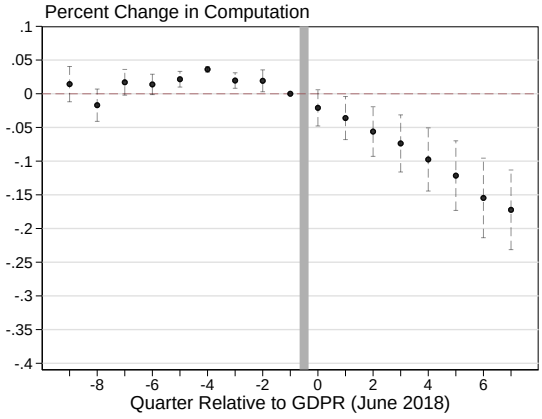
[20] Even though we have data for a few more quarters, we end our main sample in March 2020 to rule out the effects of the COVID-19 pandemic. This sample restriction also limits the potential effects of another privacy law, the California Consumer Privacy Act, which came into effect in January 2020.

Figure 3: Event Study Estimates of the Effects of the GDPR on Cloud Inputs

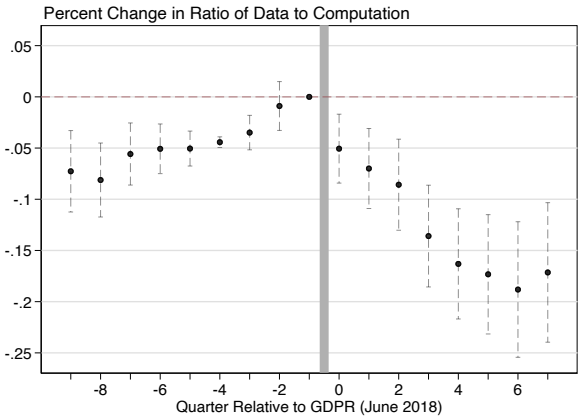
(a) Effect on Data



(b) Effect on Computation



(c) Effect on Data Intensity



Notes: Figure presents estimates of equation (1) of β_q, the coefficient on the quarter interacted with our treatment indicator. The coefficient for the quarter preceding the GDPR's implementation is normalized to zero. Dotted bars represent the 95% confidence intervals, and standard errors are clustered at the firm level. Sample sizes are presented in Table 3.

Results on Data Panel (a) of Figure 3 shows the results for data storage. First, we find no evidence of significant differential pre-GDPR trends in the US and EU, as all pre-GDPR coefficients are close to zero. We also find limited evidence for anticipation effects, which is consistent with the survey evidence that only 10% of firms expected to be compliant with the GDPR before May 2018 (Ponemon Institute, 2018). After the implementation of the GDPR, however, firms in the EU, relative to US firms, gradually decreased their data storage, with the cumulative effects growing steadily over the two years following the GDPR. The gradual rather than sudden decrease may be due to the fact that it took time for firms to implement necessary changes, as noted by Aridor et al. (2023) in the case of a large website.

The decline in data is perhaps not surprising, as the GDPR increased the cost of storing data.[21] What is perhaps more surprising, however, is the magnitude of the effect. Table 3 shows that the short-run effect is around a 12.9% decrease in data while the long-run effect doubles to around 25.7%.[22]

Results on Computation Turning towards computation, we first note that there is no clear theoretical prediction for how the GDPR should affect firms' computation decisions. The GDPR's primary goal is to protect personal data, with limited direct implications for computation. Therefore, the effect of the GDPR on computation likely depends on the elasticity of substitution between data and computation and the intensity of these inputs in the production function. If data and computation are substitutes, firms can respond to increases in data costs by substituting away from data toward computation. On the other hand, if data and computation are complements, then an increase in data cost would lead to a decrease in computation. Thus, the direction and magnitude of firm computation responses are ultimately empirical questions.

Panel (b) of Figure 3 shows that EU firms gradually decreased their computation relative to US firms after the introduction of the GDPR. The effect on computation is smaller than what we observe for data, with only a 15.4% decline two years after the GDPR. Similar to the results on data, we find no evidence of significant differential pre-GDPR trends.

The results on computation are also important because they indicate that firms do not simply eliminate (or stop accumulating) unused data. One potential explanation for our data results is that before the GDPR, firms stored data that they never utilized and subsequently deleted it to comply with the GDPR. Our findings suggest that this hypothesis is unlikely because of the substantial reduction in computation, which we conjecture would not have happened if data that was not being used were simply eliminated.[23]

Results on Data Intensity Comparisons of the magnitudes between our data storage and computation results suggest that firms became less data-intensive after the GDPR. However, in order to account for potential compositional effects, we investigate the effects of the GDPR on data intensity by using the natural logarithm of the ratio of storage to

[21] A natural concern is that these results could be purely mechanical if the GDPR simply "bans" the use of consumer data. However, while certain categories of data—such as children's data, criminal conviction data, and data revealing racial or ethnic origin—are subject to strict limitations under the GDPR (Articles 8-10), these categories were already heavily restricted under the 1995 Data Protection Directive. In this sense, the GDPR did not introduce entirely new bans on the use of consumer data; rather, it increased the cost of data collection and conditioned data processing on the existence of a lawful basis (Article 6).

[22] Importantly, firms are not necessarily deleting data, as our identification strategy relies on comparing EU and US firms. Data storage for EU and US firms could be increasing, but at different rates.

[23] This hypothesis also appears unlikely because cloud computing incurs a marginal cost for storing data, even if it remains unused. Additionally, in Section 5, we find that firms are responsive to changes in cloud prices.

Table 3: Short- and Long-Run Effects of the GDPR
(Data, Computation, and Data Intensity)

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: Log of Data			
Short-Run Effect	-0.129	-0.132	-0.125	-0.134
	(0.018)	(0.017)	(0.017)	(0.017)
Long-Run Effect	-0.257	-0.260	-0.228	-0.242
	(0.024)	(0.024)	(0.024)	(0.024)
Observations	1,143,149	1,143,149	1,143,149	1,143,149
US Firms	16,409	16,409	16,409	16,409
EU Firms	16,281	16,281	16,281	16,281
	Panel B. Dependent variable: Log of Computation			
Short-Run Effect	-0.078	-0.082	-0.132	-0.148
	(0.016)	(0.016)	(0.016)	(0.016)
Long-Run Effect	-0.154	-0.164	-0.224	-0.256
	(0.024)	(0.024)	(0.024)	(0.024)
Observations	672,942	672,942	672,942	672,942
US Firms	10,294	10,294	10,294	10,294
EU Firms	8,927	8,927	8,927	8,927
	Panel C. Dependent variable: Log of Data Intensity			
Short-Run Effect	-0.072	-0.071	-0.025	-0.021
	(0.020)	(0.020)	(0.020)	(0.019)
Long-Run Effect	-0.131	-0.126	-0.049	-0.035
	(0.029)	(0.029)	(0.029)	(0.029)
Observations	418,803	418,803	418,803	418,803
US Firms	5,487	5,487	5,487	5,487
EU Firms	5,872	5,872	5,872	5,872
Time Trends Vary By:	Industry × Pre-GDPR Size Deciles	Pre-GDPR Size Deciles	Industry	-

Notes: Table presents estimates of the short-run (δ_1) and long-run (δ_2) coefficients in Equation (2), which estimate the effect of the GDPR in the first and second year after the GDPR came into force. Column (1) presents our baseline specification, where we allow for time trends to vary flexibly across industry and pre-industry size decile interactions. Column (2) restricts these time trends so that they only vary by pre-GDPR size decile, while Column (3) only allows for variation at the industry level. Column (4) shows estimates when we include no time-trend interactions. Industries are defined as the ten divisions classified by SIC codes, with software carved out of services, for a total of eleven industries. Pre-GDPR size deciles are measured thirteen months before the GDPR. For data intensity, we define "size decile" as the interaction between storage and computation terciles when measured in the period. Standard errors are clustered at the firm level.

computation as an outcome. We estimate our specification on firms that used both types of inputs for the full year beginning exactly two years before the GDPR came into force.

Panel (c) of Figure 3 shows that firm data intensity decreased immediately after the GDPR. Panel (c) of Table 3 estimates a decrease of around 7.2% in the short run and 13.1% in the long run. Unlike the results for storage and computation, the effect on data intensity stabilizes after approximately one year.[24] The fact that firms in the EU become less data-intensive post-GDPR and decline in computation (relative to comparable US firms) suggests that storage and computation are likely complements in production, which we revisit using a production framework in Section 5.[25]

Robustness of Results There are several potential threats to our identification strategy. In Appendix D, we go through these threats and provide evidence indicating they do not drive our results. We summarize the main exercises below, and we leave the additional exercises (e.g., alternative sample definitions and empirical specifications) in Appendix D.

The most salient identification threat is that we observe only one, albeit large, cloud provider. What we observe as declines in cloud usage could simply be firms substituting usage towards other providers ("multi-cloud") or to their on-premises IT services ("hybrid cloud"). For multi-cloud, we show that our results are similar when we restrict our sample to firms that only use our cloud provider according to Aberdeen data (Table OA-2 and Figure OA-11). For hybrid cloud, we first show that our empirical exercise yields similar results for the start-up firms in our sample, which are less likely to use on-premises IT (Table OA-4 and Figure OA-13).[26] Second, we find no evidence of differential trends in interest in hybrid cloud usage—as proxied for by Google Trends—across the EU and the US.[27] Third, we show that EU firms are less likely to leave the cloud relative to the US firms after the GDPR (Figure OA-16). Therefore, it is unlikely that the declines we observe are

[24] An additional implication of the gradual adjustment in data and computation usage is that our estimates may not capture longer-run impacts, which could continue to unfold after our sample ends in March 2020. To assess this concern, we re-estimate the coefficients by extending the sample by three additional quarters in Figure OA-18 and find that the effect sizes begin to stabilize in late 2020 and early 2021. While these patterns provide some evidence on the longer-run effects, we prefer not to overinterpret these results, as this period coincides with the COVID-19 pandemic and the introduction of the California Consumer Privacy Act, which could confound the event-study estimates. For this reason, we do not use the extended sample as our main specification.

[25] Table 3 also shows the robustness of including flexible time trends by industry and size-decile fixed effects. We observe that excluding the pre-GDPR size fixed effects results in similar storage estimates, slightly higher (in absolute value) computation estimates, and lower data intensity estimates. These differences likely reflect compositional variations in treatment responses by firm size between EU and US firms.

[26] See Jin and McElheran (2017) and Ewens et al. (2018) for research supporting this assumption.

[27] Figure OA-14(a) shows no differential time trends in hybrid cloud-related searches between the US, the UK, or Germany, which is suggestive that differential uptake of hybrid cloud services in the EU is unlikely to explain our results. Furthermore, hybrid cloud remains an order of magnitude less popular as a search term than cloud computing (Figure OA-14(b)). See Appendix D.1 for more information.

simply driven by substitution to on-premises IT.

Another natural explanation for our results is the possibility of differential price trends in the EU and the US. If cloud prices increase in the EU relative to the US post-GDPR (perhaps to cover GDPR compliance costs, for example), we could see a decline in data and computation even without the GDPR having any additional effects on firms. To check this hypothesis, we use the paid prices for cloud storage as a dependent variable and find no differential price changes between the EU and the US (Figure OA-15).

We also consider whether our results are particularly driven by websites' cookie consent notices and the clauses governing the collection and storage of data from websites. We might expect firms with active website use—which we proxy for through the usage of cloud-based web services—to be more affected by the policy than those without. Table OA-5 shows larger effects among firms that used web services in storage and computation. However, we find that the data and computation adjustments of web users and non-web users are proportional and that their reductions in data intensity are similar.[28]

4.3 Heterogeneity

By Industry The relationship between data and computation may vary by industry, depending on how each industry incorporates data inputs into its production processes. For this reason, we investigate whether the effects of the GDPR on data and computation vary across four mutually exclusive and exhaustive industry groups: software, services, manufacturing, and all other industries. Table 4 shows our estimates of the short- and long-run effects of the GDPR when we estimate Equation (2) across different industry groups.[29] One striking result is the breadth of our results: we find declines in data, computation, and data intensity across all industry groups. This suggests that the direct impact of the GDPR extends beyond the subset of previously studied industries or mechanisms—e.g., websites or venture capital investments—to affect firms across all industries.[30]

Furthermore, we find substantial heterogeneity between industries in the magnitudes of the effects. Panel A shows that the most significant decreases in data in response to the GDPR come from manufacturing firms (40.4% in the long run), followed by software firms (25.3%), and services firms (18.0%). Similarly, Panel B shows that for computation, the fall

[28] Another potentially important channel through which the GDPR may operate is firms' geographic expansion decisions, specifically the probability that domestic firms become multinational. We analyze this effect through an event study using the probability of becoming multinational as the outcome variable and find no differential multinational propensity between U.S. and EU firms, as reported in Figure OA-8.

[29] We show the quarterly dynamics in Figures OA-1 and OA-2, and the (lack of) pretrends at the industry level.

[30] This result also suggests that the main mechanism behind our findings is not simply a decline in venture capital investment in the EU following the GDPR, as emphasized in the literature (Jia et al., 2021; Janßen et al., 2021), since many industries in our sample are less likely to receive venture capital investment.

Table 4: Short- and Long-Run Effects of the GDPR
(Heterogeneous Effects by Industry)

	Baseline	Software	Services	Manufacturing	Other Industries
	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent variable: Log of Data					
Short-Run Effect	-0.129	-0.113	-0.080	-0.259	-0.190
	(0.018)	(0.035)	(0.026)	(0.063)	(0.037)
Long-Run Effect	-0.257	-0.253	-0.180	-0.404	-0.354
	(0.024)	(0.048)	(0.036)	(0.086)	(0.051)
Observations	1,143,149	291,781	486,457	94,612	270,299
US Firms	16,409	3,196	8,141	1,141	3,931
EU Firms	16,281	5,150	5,912	1,508	3,711
Panel B. Dependent variable: Log of Computation					
Short-Run Effect	-0.078	-0.078	-0.048	-0.171	-0.077
	(0.016)	(0.032)	(0.024)	(0.051)	(0.033)
Long-Run Effect	-0.154	-0.150	-0.100	-0.322	-0.163
	(0.024)	(0.050)	(0.037)	(0.073)	(0.049)
Observations	672,942	165,752	270,846	65,532	170,812
US Firms	10,294	2,050	4,623	900	2,721
EU Firms	8,927	2,747	3,204	914	2,062
Panel C. Dependent variable: Log of Data Intensity					
Short-Run Effect	-0.072	-0.084	-0.084	-0.078	-0.043
	(0.020)	(0.042)	(0.031)	(0.066)	(0.039)
Long-Run Effect	-0.131	-0.196	-0.161	-0.043	-0.069
	(0.029)	(0.064)	(0.045)	(0.097)	(0.055)
Observations	418,804	103,606	168,020	41,449	105,729
US Firms	5,487	1,054	2,473	496	1,464
EU Firms	5,872	1,755	2,123	610	1,384

Notes: Table presents estimates of Equation (2) of δ_1 and δ_2, re-estimated across for various industry divisions. For comparison, Column (1) presents our baseline estimates across all industry divisions. Column (2) restricts our sample to software firms, which are defined through SIC codes 7370 - 7377. Column (3) restricts the sample to services firms, Column (4) restricts the sample to firms in the manufacturing division, and Column (5) presents estimates on the remaining firms in the sample (non-software, non-services, and non-manufacturing industry divisions). Standard errors are clustered at the firm level.

is largest in magnitude for manufacturing (32.2% in the long run), followed by software (15.0%) and services (10.0%).

While it may seem surprising that industries like software and services firms exhibit more muted responses to the GDPR than manufacturers, this may reflect several factors. First, manufacturers are still subject to the GDPR if they sell directly to customers, employ workers in the EU, or work with EU suppliers or trading partners. Second, manufacturers might be able to substitute compute and data with other inputs more easily in response to the GDPR because data and computation are less essential parts of their production than software and services firms. Alternatively, they might be less sophisticated in terms of their existing data infrastructure and comply with the GDPR by simply reducing data usage. We provide additional discussion and supporting evidence that explains the larger effects for manufacturers in Appendix B.4.[31]

Finally, Panel C of Table 4 shows results for data intensity. We find that data intensity decreases in all industries, although the standard errors are large for some of these estimates. Our point estimates suggest that long-run data intensity decreases the most in the industries that experienced the smallest declines in storage and computation.

By Regulatory Stringency Although the GDPR harmonized data protection regulations across the EU, enforcement was delegated to each country's data protection authority. Thus, enforcement policies can vary across countries due to differences in resources available to data protection authorities and their approaches to data protection (Johnson, 2022). Because of these differences, we might expect firms in countries with more lenient regulators to respond less to the GDPR. To test this hypothesis, we use a measure of perceived regulatory strictness created by Johnson et al. (2023) using data from European Commission (2008) that varies at the country level. This measure calculates a z-score for each country based on firms' stated perceptions of their country's relative data protection regulatory strictness.[32] We then classify each firm as above or below the normalized median strictness in the survey according to the strictness of their country's regulator.

We modify Equation (2) by introducing two additional coefficients to account for potential heterogeneity by regulatory stringency. Specifically, we interact a categorical variable indicating above-median stringency with the EU categorical variable to measure the short- and long-run differences in Y_{it} for EU firms across different levels of regulatory stringency.

Table 5 summarizes these results. Although interaction coefficients are not statistically

[31] For some commercial products offered to manufacturers for GDPR compliance, see GrowthDot and GroundLabs. For an overview of how GDPR applies to manufacturers, see Data Protection Laws for Manufacturers.

[32] One limitation of this index is its reliance on surveys rather than actual enforcement. To our knowledge, no country-level index provides a systematic measure of enforcement based on observed regulatory activity.

Table 5: Short- and Long-Run Effects of the GDPR by Regulatory Strictness

	Data (1)	Computation (2)	Data Intensity (3)
		Main Effects	
Short-Run	-0.116	-0.064	-0.072
	(0.038)	(0.029)	(0.035)
Long-Run	-0.206	-0.155	-0.138
	(0.048)	(0.042)	(0.048)
		Interactions (Above-Average Strictness)	
Short-Run	-0.024	-0.047	0.009
	(0.038)	(0.030)	(0.036)
Long-Run	-0.063	-0.030	0.008
	(0.048)	(0.043)	(0.049)
Observations	1,143,114	672,927	473,977
US Firms	16,409	10,294	6,412
EU Firms	16,281	8,927	6,422

Notes: Table presents estimates of Equation (2) with an additional term to measure the effect of above-median GDPR strictness. The short-run term captures the triple interaction of the short-run post-GDPR coefficient, the EU categorical variable, and a categorical variable indicating firms in the above-median regulatory stringency countries. The long-run term repeats the same procedure but uses the long-run post-GDPR period instead. Regulatory strictness is measured according to Johnson et al. (2023) using data from European Commission (2008). For data intensity, we define "size decile" as the interaction between data and computation terciles when measured in the period. Standard errors are clustered at the firm level.

significant at conventional levels, the point estimates are negative for data and computation, suggesting that firms in countries with above-median regulatory strictness may face larger declines in these inputs. In the short run, data decreases by 2.4 pp. more in above-median strictness countries than in below-median ones, while computation declines by 4.7 pp. more. In the long run, data and computation go down by 6.3 pp. and 3.0 pp. more in above-median strictness countries, respectively. While these estimates are imprecise and should be interpreted with caution, the negative signs on data and computation suggest that regulatory stringency may be associated with larger declines in these inputs beyond the presence of privacy regulation alone.[33]

4.4 Discussion

Our findings suggest that EU firms responded to the GDPR by storing less data, performing less computation, and becoming less data-intensive compared to US firms. These results provide direct and large-scale evidence that firms comply with the GDPR by adjusting their data inputs. Moreover, the results are not driven by a single industry or websites

[33]Figure OA-7 in the Appendix provides visual evidence of this relationship by plotting country-level stringency against the estimated effects on data, compute, and data intensity.

affected by cookie consent policies, indicating the far-reaching implications of the GDPR.

However, these findings do not offer a comprehensive understanding of the economic costs imposed on firms. Such an analysis requires understanding the role of data in firm production and considering firms' adjustment margins in response to privacy regulations. We therefore turn to a more structural approach that allows us to translate these behavioral responses into economically meaningful cost measures.

5 A Model of Production with Data

This section introduces a production function framework with data and computation and estimates its parameters. We use our framework to study both how firms use data and computation in production and how privacy regulations might affect these decisions. We model the GDPR as a wedge between the cost of storing data and the total (perceived) cost of data that includes regulatory costs. We focus on estimating the size of this wedge, corresponding increases in production costs, and their implications for firms.

5.1 Production Function with Data

Firm i in month t produces output Y_{it} by combining compute (C_{it}), data (D_{it}), and other inputs (X_{it}) in a given industry (software, services or manufacturing):

$$Y_{it} = F\big(X_{it}, I_{it}(C_{it}, D_{it}\big), \omega_{it}),$$

where the function $I_{it}(\cdot)$ aggregates compute and data inputs to be used in firm production and ω_{it} is firm productivity. It is natural to model the contribution of data and computation to firm production in this way, as these inputs are inherently interdependent: firms use computation to process data, and the processed data is then combined with other inputs. We assume a CES functional form for the aggregation of data and computation:

$$I_{it}(C_{it}, D_{it}) = \left(\omega_{it}^{c} C_{it}^{\rho} + \alpha D_{it}^{\rho}\right)^{1/\rho}, \tag{3}$$

where ω_{it}^{c} is a scalar representing the compute-augmenting productivity, α denotes data intensity, and $\sigma = 1/(1-\rho)$ is the elasticity of substitution between data and compute.[34] While CES imposes parametric assumptions, it offers flexibility in the elasticity of substitution, the key parameter that governs how firms re-optimize their inputs in response to

[34] As we will show later, α can be normalized without loss of generality because the ratio of ω_{it}^{c} to α serves as a sufficient statistic that determines the relative intensity of compute and data in production. We retain α in the notation to highlight the role of data intensity in the derivations we will present later.

the GDPR. We discuss the flexibility of the CES specification in greater detail in Appendix E.2. We refer to the intermediate input $I_{it} = I_{it}(C_{it}, D_{it})$ as "information" throughout our analysis.[35]

Our empirical analysis will primarily use the CES model of data and compute aggregation in Equation (3) rather than the full production function. This choice is motivated by the lack of a standardized framework for modeling data in firm production. For example, data could increase overall firm productivity (Jones and Tonetti, 2020), serve as an input in production (Bessen et al., 2022), increase labor productivity (Agrawal et al., 2019), and increase revenue by better customer targeting (Eeckhout and Veldkamp, 2022).[36] While this limits potential counterfactual analyses we could perform, we consider it a reasonable trade-off given our study's large-scale coverage across firms and industries.

Our production function model in Equation (3) includes a firm-specific compute-augmenting productivity term, ω_{it}^c, to capture heterogeneity in information production technology across firms. This heterogeneity can arise from two main sources. First, firms may differ in their inherent production technologies regarding how much data they need, making production more data-intensive for some firms than others. Second, even with similar underlying technologies, firms may achieve different levels of compute productivity through differences in resources they have, including technical infrastructure and human capital (e.g., advanced software tools and skilled engineers). The large firm-level variation in data intensity that we documented in Figure 2 underscores the importance of accounting for these technological differences.

Our approach relies on estimating input demand functions derived from the CES form under the assumption that firms choose data and computation to minimize static production cost of I_{it}, taking ω_{it}^c as given. In particular, we assume that C_{it} and D_{it} are variable inputs that firms optimize every period. We view this assumption as reasonable for cloud computing given that firms can easily adjust their usage of storage and computation and provide a microfoundation in Appendix E.1. We also assume that firms are price-takers in the input markets for C_{it} and D_{it}, which is again a reasonable assumption for cloud

[35] Information I_{it} lacks a natural unit in the production function shown in Equation (3). This is because any monotone transformation $h(\cdot)$ of the information production function can be offset by applying $h^{-1}(I)$ inside the F function. However, as we show in Appendix F.4, this scale invariance does not affect our identification strategy for wedges and associated production cost increases as we focus on changes in firms' costs due to the GDPR rather than their levels. This robustness to monotone transformations also accommodates information production to have non-constant returns to scale through the transformation $h = I^\theta$. However, we note that our empirical strategy does not identify the returns to scale parameter.

[36] More formally, our setting covers: (i) $Y = f(X)\omega(I)$ (productivity increasing), (ii) $Y = f(X, I, \omega)$ (input in production), (iii) $Y = f(X, \omega^L(I) \cdot L, \omega)$ (labor-augmenting), and (iv) $R = p(I)f(X, \omega)$ (price discrimination). In these examples, Y and R are output and revenue; ω^L is labor-augmenting productivity, and p is the output price. In each specification, information affects a different part of the production function.

computing because firms typically pay a linear price by the hour.[37] Overall, this static cost minimization assumption enables us to bypass the dynamics of firms' decision-making, which would necessitate additional assumptions.

We use p^c_{it} and p^d_{it} to denote the input prices for compute and data, which may vary across firms, as we explain later. Based on the cost minimization assumption, we derive the following first-order condition (FOC) for firms' ratio of compute and data choices from the CES production function:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma + \sigma \log\left(\frac{p^d_{it}}{p^c_{it}}\right) + \sigma \log(\omega^c_{it}), \tag{4}$$

where $\gamma = -\sigma \log(\alpha)$. We provide the complete derivations in Appendix F.1 and also show in Appendix F.2 that we obtain the same FOC if we were to include labor (e.g., software engineers) in the information production function. We note that the level of ω^c_{it} is not separately identified in this equation from α, so we normalize α to 1 in the estimation.

According to this FOC, the relationship between input ratios and input prices is governed by the elasticity of substitution. A key feature of this equation is that the elasticity of substitution and compute-augmenting productivity can be estimated from firms' input demand functions alone, without requiring data on other inputs or outputs. This property of the CES functional form has been commonly used in the literature for estimating the elasticity of substitution (Doraszelski and Jaumandreu, 2018; Raval, 2019; Demirer, 2025).

Although our framework extends the production function literature by incorporating computation and data, it has certain limitations. While we account for potential variations in data quality across firms through ω^c_{it}, we assume that data is homogeneous within each firm. This limitation becomes particularly relevant if, for instance, firms have data types with varying levels of quality, and the GDPR impacts the composition of data. Relaxing this assumption requires incorporating different data types into the production function, which we do not observe. It is worth noting, however, that the assumption of homogeneous inputs within a firm is a common practice in the production function literature.

5.2 The GDPR as a Cost Shock to Data

We model the GDPR as a cost shock to data input—as we have extensively argued data is the main focus of GDPR regulations. While some aspects of the GDPR do pertain to computation (e.g., Article 30, records of processing activities), the effects of the regulation

[37] An exception is very large firms, which can negotiate their prices bilaterally. Since we focus on domestic firms, this exception likely affects a very small fraction of our sample. See footnote 40 for more information.

on data are significantly larger, and computation is less salient to regulators than data.

As mentioned before in Section 2 and in Appendix B.2, the GDPR increased the fixed and variable costs of using data. For example, customer data-rights requests under the GDPR may impose variable costs on firms that increase with the amount of data. Similarly, the probability of a data breach and penalties in case of non-compliance likely increase with the amount of data firms have.[38] By contrast, fixed costs are one-time expenses that do not vary with data amount—e.g., hiring data protection officers and developing a data protection management system. Since fixed costs do not affect input demand in the intensive margin, we focus on modeling the variable cost.

We make the following assumptions about data costs before and after the GDPR:

$$\textbf{Pre-GDPR:} \quad \tilde{p}_{it}^{d} = p_{it}^{d}, \qquad\qquad \textbf{Post-GDPR:} \quad \tilde{p}_{it}^{d} = (1 + \lambda_i) p_{it}^{d}.$$

Here, p_{it}^{d} represents the variable cost of data without the GDPR (i.e., the cost of storing data paid to the cloud provider), and $\tilde{p}_{it}^{d}$ is the cost after accounting for the regulatory costs introduced by the GDPR. Therefore, λ_i denotes the wedge between the actual cost of data and the total variable cost that includes complying with the GDPR. We follow the literature and model λ_i as a multiplicative wedge (e.g., Chari et al., 2007; Hsieh and Klenow, 2009). This wedge is firm-specific because compliance costs are likely to be heterogeneous across firms, depending on their size and the types of data they collect. Alternatively, we can also interpret λ_i as each firm's perceived cost of the GDPR, as they may hold different beliefs about enforcement or have varying levels of risk aversion that affect the expected cost of liability in the event of a data breach (Ganglmair et al., 2024).

Although we have modeled the GDPR as affecting the variable cost of data, we show in Section F.3 that our estimation procedure is consistent with several other interpretations of the GDPR. First, we show that if there are other unobserved variable costs to data that generate wedges before the GDPR, our estimate captures the additional wedges driven by the GDPR. Second, we consider an alternative information production function with data-augmenting productivity where the GDPR generates a negative shock to this productivity by reducing the effectiveness of data. We demonstrate that our estimation procedure approximately recovers the size of this negative productivity shock in such a model. Finally, if the GDPR generates wedges in compute in addition to data, our wedge estimate will recover the ratio of data-to-compute wedges, making our estimate of costs conservative.

[38] This observation aligns with the fact that larger firms tend to receive more substantial fines in our fine data.

5.3 Identification of Parameters

Our end goal is to estimate the production function parameters and the firm-level wedges introduced by the GDPR. To illustrate the potential identification problems when estimating these objects, consider the FOC in Equation (4) after the GDPR for EU firms:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma + \sigma \log\left(\frac{p^d_{it}}{p^c_{it}}\right) + \sigma \log(1 + \lambda_i) + \sigma \log(\omega^c_{it}). \tag{5}$$

This FOC reveals a fundamental identification challenge: the GDPR wedge, λ_i, cannot be separately identified from a level shift in ω^c_{it} post-GDPR. Intuitively, firms may decrease their compute-to-data ratio either because their compute-augmenting productivity has increased or because the GDPR has imposed additional data costs. Without additional assumptions, we cannot distinguish these two cases using our data. To this end, we impose the assumption that compute-augmenting productivity can be decomposed as follows:

$$\log(\omega^c_{it}) = \log(\omega^c_i) + \log(\phi^c_t) + \log(\eta_{it}). \tag{6}$$

Here ω^c_{it} is decomposed into a firm-specific component (ω^c_i) that is mean-zero (in logs), an industry-specific time trend (ϕ^c_t) that shifts the level of compute-augmenting productivity in the industry, and a mean-zero idiosyncratic component (η_{it}). This decomposition suggests that we need to control for ω^c_i and ϕ^c_t to identify the wedges generated by the GDPR.[39]

Our identification strategy therefore involves two steps. In the first step, we recover ω^c_i and ϕ^c_t using data from EU firms in the pre-GDPR period and data from US firms, respectively. In particular, we assume that firm-specific compute technology does not change after the GDPR and that each EU industry follows the same compute-technology trend as the same industry in the US. With these assumptions, we can control for firm-specific compute-augmenting technology in the second step and estimate the GDPR wedge as a percentage of the observed data storage cost. We explain each of these steps below and provide more detail in Appendix G.3.

[39] While we estimate the production function separately for three broad industry groups (software, manufacturing, and services), we allow ϕ^c_t to vary at the 2-digit SIC industry level within each group. To avoid introducing additional notation, we do not index ϕ^c_t by 2-digit industry explicitly; see Appendix G.3 for a formal description of the estimation procedure.

5.3.1 First Step: Identification of Compute Productivity and Elasticity of Substitution

To estimate the elasticity of substitution and compute-augmenting productivity, we use pre-GDPR data and estimate the following equation:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma_1 + \sigma_1 \log\left(\frac{p^d_{it}}{p^c_{it}}\right) + \sigma_1 \log(\omega^c_i) + \sigma_1 \log(\phi^c_t) + \sigma_1 \log(\eta_{it}), \tag{7}$$

where σ_1 is the pre-GDPR elasticity of substitution. Two important considerations arise when estimating this equation. First, the estimation requires variation in the data-to-compute price ratio across firms over time. Second, these prices might be correlated with unobservable productivity shocks (η_{it}). To address this endogeneity, it is important to understand the factors generating price variation in cloud computing.

Cloud computing prices typically vary depending on the region where the data center is located. These posted prices can be considered orthogonal to the firm-level idiosyncratic compute-augmenting productivity shocks (η_{it}) because it is unlikely that any single firm is large enough to affect them conditional on ϕ^c_t. In addition, cost improvements and increased competition were the main drivers of price changes in the last decade (Byrne et al., 2018). However, the prices that firms pay may differ from these posted prices for two reasons. First, firms may have differential preferences over data center locations based on distance. Second, firms may receive a percentage discount from the listed price based on long-term commitments.[40] These two sources of price variation can create endogeneity because, for example, firms with a high compute-augmenting productivity shock may switch between data centers based on price differences, or they may receive long-term commitment discounts. We address these potential sources of endogeneity by developing a shift-share design (Bartik, 1991; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022).

We first introduce the broad intuition behind our instrument. Our approach aims to address potential endogeneity in prices by leveraging two features of our data. First, because we observe both list prices and paid prices, we can use changes in list prices as

[40] Cloud providers offer discounts if firms commit to using cloud resources over a specific period of time (typically one or three years). These discounts are called "reserved instance" or "committed use" discounts, depending on the provider. These discounts are applied to the list prices and are the same across customers except for very large customers, who might individually negotiate prices. A survey of 750 companies conducted in 2023 finds that only one-third of them use these discounts (Flexera, 2023), which is likely lower during our sample period and among domestic firms. Moreover, firms that receive long-term commitment discounts can resell or refund their commitments for a fee in most major cloud providers (AWS Reserved Instance Marketplace). Therefore, we believe that linear prices are a good approximation for firms' monthly decisions of storage and computation. For examples of these pricing policies, see AWS Reserved Instance Market and Azure Reserved VM Instances. We provide more information about cloud computing pricing in Appendix G.1.

an instrument for the changes in paid prices. These changes are still predictive of the prices that firms face because discounts are applied to list prices. Second, we construct a measure of exposure to specific data centers for each firm and period. We use historical exposure shares rather than contemporary ones because previous data center choices are sunk. However, previous data center choices remain predictive of current data centers firms use due to switching costs, as transferring data between locations is time-consuming and costly, especially for large datasets. As a result, firms' data center location choices are highly persistent over time.

More formally, the shift-share design combines list prices with variations in firms' pre-existing data center location choices. We construct instruments z_{it}^{d} and z_{it}^{c} for the data storage and computation prices each firm i faces at time t. The exposure shares in a given period are calculated as the ratio of firm i's usage in a specific data center to its total usage across all data centers. These exposures yield the following equation for the instrument:

$$z_{it}^{\{c,d\}} = \sum_{l \in \mathscr{L}} s_{il(t-10)}^{\{c,d\}} p_{lt}^{\{c,d\}} \tag{8}$$

where $s_{il(t-10)}^{\{c,d\}}$ denotes firm i's usage share for data center location l as measured 10 months before t, $p_{lt}^{\{c,d\}}$ is the price index for each service in location l at time t, and $\mathscr{L}$ denotes the set of data center locations.[41] Our exposure shares are lagged by 10 months because contemporaneous shares are susceptible to reverse causality. While shift-share instruments can be driven by assumptions about either the exogeneity of "shares" or the independence and exogeneity of "shocks" (Borusyak et al., 2022), the identifying assumption underlying our exposure shares is most similar to the "shares" assumption discussed in Goldsmith-Pinkham et al. (2020). In particular, the exclusion restriction underlying our shift-share design is that contemporary shocks to each firm's compute-augmenting productivity are exogenous to changes in the ratio of list prices of cloud computing in the firm's historical data center choices, controlling for industry-specific trends.[42]

We use z_{it}^{c}/z_{it}^{d} as an instrument for price ratio p_{it}^{d}/p_{it}^{c} and estimate Equation (7) for three EU industries (software, services, and manufacturing) separately using pre-GDPR data, as the pre-GDPR data does not include a regulatory wedge. This allows us to estimate

[41] We provide more detail on our price index construction in Appendix G.2.

[42] One example of a potential threat to identification would be if η_{it} is correlated over time after accounting for aggregate industry time trends, and this caused firms to select data centers with specific trends in the ratio of prices. However, given that our model is estimated using price ratios rather than direct price levels, and that forecasting data center-specific trends in these price ratios is difficult, we view our identification assumption as reasonable in this setting. We provide further details for the instrumental variable construction in Appendix G.2.

compute-augmenting productivity (ω_i^c) and elasticity of substitution parameters before the GDPR. We also estimate Equation (7) for US industries over the entire sample period, as US firms do not experience any regulatory distortion. This allows us to recover the industry-specific compute-augmenting productivity trends, ϕ_t^c, for US industries.

5.3.2 Second Step: Identification of the Cost of the GDPR

In the second step, we use the EU post-GDPR data to estimate the wedges generated by the GDPR and the EU post-GDPR elasticity of substitution between compute and data.[43] Incorporating this into the firm's input demand function, we obtain the following equation:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma_2 + \sigma_2 \log\left(\frac{p_{it}^d}{p_{it}^c}\right) + \sigma_2 \log(1+\lambda_i) + \sigma_2 \log(\omega_i^c) + \sigma_2 \log(\phi_t^c) + \sigma_2 \log(\eta_{it}), \quad (9)$$

where σ_2 is the post-GDPR elasticity of substitution. Here, unlike in the pre-GDPR period, GDPR wedge, λ_i, affects the compute-to-data ratio: a higher λ_i leads firms to substitute away from data toward compute. To use this equation for identifying λ_i, we make the following assumptions:

Assumption 1. *Firms' compute-augmenting productivity (ω_i^c) remains the same after the GDPR.*

We note that this assumption still allows for industry-specific trends in compute due to $\log(\phi_t^c)$ in Equation (9). The assumption also does not restrict firms' ability to respond to the GDPR by changing their compute-to-data ratio. Rather, it implies that the firm-specific component of the underlying information production technology remains the same.

At this point, it is worth comparing our approach to the approaches taken in the literature that estimate distortionary wedges. The large literature on misallocation identifies distortions as the difference between the marginal product of an input and its price (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). This literature assumes that production technology is the same across firms up to Hicks-neutral productivity because otherwise, the firm-specific wedges cannot be distinguished from arbitrary firm-level heterogeneity in production technology. We face the same identification problem but take a different approach. Instead of assuming homogeneous production technology, we allow for heterogeneity through compute-augmenting productivity but assume that this heterogeneity is time-invariant within a window of a few years. We note that both approaches have strengths and weaknesses, but we believe that in our context, it is essential to allow for heterogeneous production technology.

[43] We allow elasticity of substitution, σ, to differ before and after the GDPR for two reasons: (i) the technology governing how firms combine data and computation may evolve over time due to algorithmic advances, and (ii) the policy itself may alter how firms combine these inputs.

We also differ from the misallocation literature by analyzing input demand functions for two variable inputs—one distorted and one undistorted—instead of estimating a full production function. In our approach, we can net out the sources of distortions common to both inputs, such as market power, and recover the distortion specific to the data input. This identification strategy is similar to the approach used in the literature to identify input market power from the two variable inputs (Morlacco, 2020; Kirov and Traina, 2023).

Assumption 2. *In the absence of the GDPR, EU and US industries would have followed the same time trends in aggregate compute-augmenting productivity.*

This is the second assumption necessary for identifying the GDPR wedges by controlling for industry-level changes in compute-augmenting productivity.[44] Otherwise, any level shift in the compute-to-data ratio of EU firms post-GDPR may be attributed to arbitrary changes in aggregate compute-augmenting productivity in the EU. Therefore, we use the estimated post-GDPR industry trend from the US firms to control for industry trends in the EU. The parallel trends we find within industries before the GDPR in our reduced-form results support this assumption (Figures OA-1, OA-2, and OA-3).

With these two assumptions, we can estimate the following equation:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma_2 + \sigma_2\left(\log\left(\frac{p^d_{it}}{p^c_{it}}\right) + \log(\hat{\phi}^c_t)\right) + \sigma_2\left(\log(1+\lambda_i) + \log(\hat{\omega}^c_i)\right) + \sigma_2 \log(\eta_{it}), \quad (10)$$

where $\hat{\omega}^c_i$ denotes estimates of compute-augmenting productivity using EU pre-GDPR data and $\hat{\phi}^c_t$ denotes the estimates of compute-augmenting productivity trend of the US firms. By estimating this equation using EU firms' post-GDPR data, we can identify our main object of interest (λ_i) along with the post-GDPR elasticity of substitution.[45] Our specification, therefore, allows for changes in the elasticity of substitution post-GDPR. To account for the uncertainty in the two-step estimation procedure, we calculate standard errors via a bootstrap procedure that treats firms as independent observations and resamples firms with replacement within industries over 250 repetitions. We provide the details of the estimation procedure in Appendix G.

[44] This assumption does not imply that industry-level components of data costs are the same in the US and EU after the GDPR. Rather, we assume that their counterfactual trends (in the absence of the GDPR) would have evolved similarly over time, while a non-zero mean of λ_i can generate a level shift in data costs in the EU industries relative to the US industries. In particular, one can decompose $\lambda_i = \lambda + \Delta\lambda_i$ where λ corresponds to industry-level cost increase whereas $\Delta\lambda_i$ is mean zero firm component.

[45] Appendix G.4 provides useful intuition behind the identification of λ_i. Roughly speaking, the estimated wedges capture the variation in data intensity (the ratio between inputs) among comparable EU and US firms that is not explained by changes in prices, changes (over time or across regions) in the elasticity of substitution, or differences in compute-augmenting productivity.

Table 6: Elasticity of Substitution Results by Industry

Industry	Software		Services		Manufacturing	
	OLS	IV	OLS	IV	OLS	IV
Elasticity of Substitution (σ_1)	0.46	0.44	0.45	0.41	0.37	0.32
	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.04)
First-Stage (Instrument)	-	0.16	-	0.15	-	0.18
	-	(0.00)	-	(0.00)	-	(0.01)
Firm FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓
F-Stat	-	5,197	-	5,718	-	2,057
Observations	107,580	107,580	132,217	132,217	45,301	45,301

Notes: Table presents our estimation results of the elasticity of substitution between data and compute across industries. Estimates are presented for EU firms using the full sample. Standard errors are calculated using 250 bootstrap repetitions at the firm level.

6 Production Function Estimation Results

This section provides results on the elasticity of substitution between data and compute, the wedges introduced by the GDPR, and how these wedges affect firms' production costs.

6.1 The Elasticity of Substitution Between Data and Computation

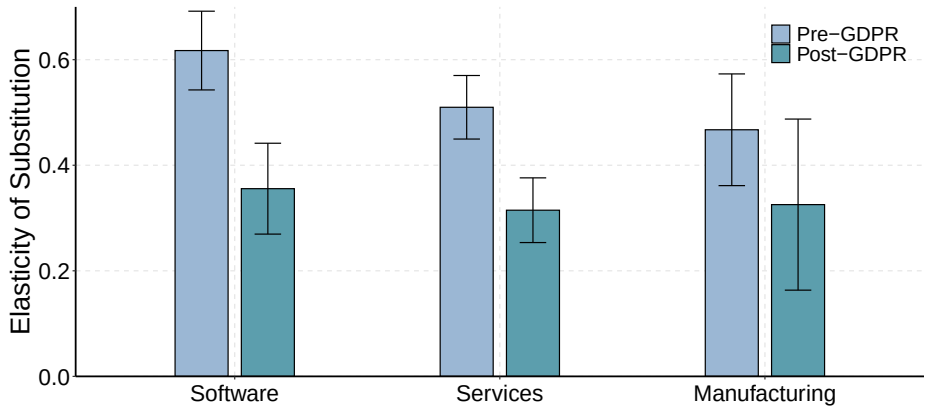
We begin by presenting estimates of the elasticity of substitution for EU firms. Table 6 presents these elasticities for three industries separately—software, services, and manufacturing—using both OLS and IV estimates.[46] We also present the first-stage estimates for each industry and their associated F-statistics. The first-stage coefficients are positive, indicating a positive relationship between our shift-share instruments and the contemporaneous prices faced by firms. Our results also indicate F-statistics in the thousands, suggesting that our instruments strongly correlate with the endogenous variables.

Our estimates suggest that data and compute are strong complements in all industries, with the estimated elasticities ranging from 0.32 to 0.44. The larger magnitudes in the software industry suggest that software firms can more easily substitute between data and compute. Furthermore, our IV estimates are smaller than the OLS ones. This bias is consistent with our intuition that firms with higher compute-augmenting productivity may be more likely to search for lower relative computation prices.

We also assess whether the GDPR led to any change in production technology in

[46] We exclude "other industries" analyzed in the event study from the production function analysis because we do not want to impose a single production function for different industries. This sample also conditions on firms with active usage of data and compute in both the pre- and post-GDPR periods to be able to estimate the wedges.

Figure 4: Elasticity of Substitution Between Data and Compute for EU Firms



Notes: Figure presents our estimation results of the elasticity of substitution between data and compute (σ) across industries, and we present separate estimates for the pre- and post-GDPR (σ_1 and σ_2, respectively). Solid lines denote the 95% confidence intervals, and standard errors are calculated using 250 bootstrap repetitions at the firm level.

Figure 4, which separately reports the elasticity of substitution estimates before and after the GDPR for EU firms. We find a statistically significant decline in the elasticity of substitution in the services and software industries, suggesting that GDPR affected firms' production technology by making data and computation closer complements.[47]

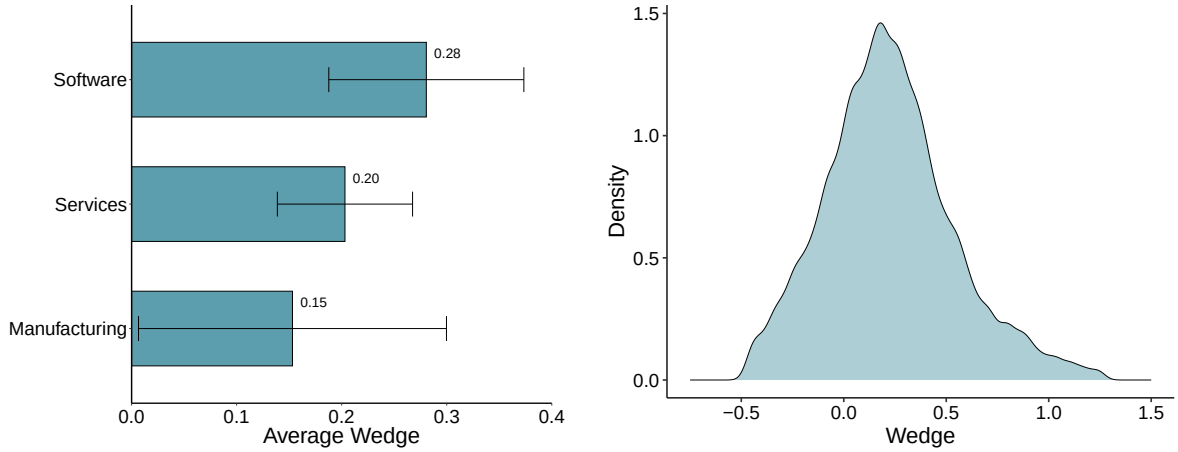
Finally, we compare our estimated elasticity of substitution between data and compute to the existing elasticity of substitution estimates of other inputs to understand how the IT inputs differ from traditional inputs. While the estimates vary, they range from 0.3 to 0.7 for capital and labor (Caballero et al., 1995; Chirinko, 2008; Raval, 2019) and from 1.5 to 3 for labor and intermediate inputs such as materials (Chan, 2023; Peter and Ruane, 2023). This indicates that data and compute are more complementary than traditional inputs. We view these estimates as a contribution to the production function literature, given the limited empirical evidence on how firms use data despite its growing importance.

6.2 The Regulatory Wedge Induced by the GDPR

Next, we examine our estimates of the wedges introduced by the GDPR (λ_i). Panel (a) of Figure 5 displays the average wedge for EU firms across industries together with the 95% confidence intervals. The estimates are statistically significant and range from 15.3% (manufacturing) to 20.3% (services) to 28.1% (software), with an average of 22.4%, implying that the GDPR raised the cost of data for firms. The wedge is the highest for software firms,

[47] In Figure OA-4, we repeat this exercise for US firms for comparison. We find comparable elasticities of substitution for firms in the US before and after the GDPR.

Figure 5: Wedge Estimates



(a) Average Wedge by Industry

(b) Wedge Distribution

Notes: This figure presents our estimation results for the wedge induced by the GDPR (λ_i). Panel (a) presents the average estimated wedge for firms within each industry. Panel (b) presents the full distribution of estimated wedges. Solid lines denote the 95% confidence intervals, and standard errors are calculated using 250 bootstrap repetitions at the firm level.

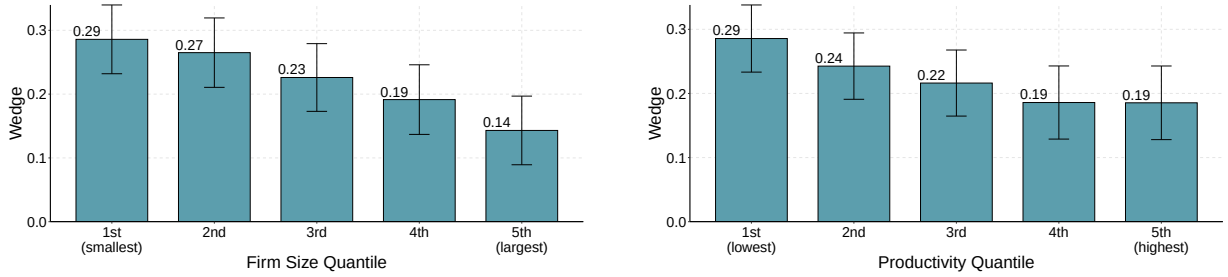
likely due to their higher exposure to GDPR compliance requirements.[48] These average estimates, however, hide substantial firm-level heterogeneity. As shown in Panel (b) of Figure 5, there is considerable heterogeneity in the wedge generated by the GDPR. For some firms, the wedge is close to zero, while for others, it can be as large as one.[49]

To better understand this heterogeneity and to study the determinants of these regulatory wedges, we look at how they correlate with two firm-level characteristics: (i) firm size, as measured by the number of employees, and (ii) compute-augmenting productivity, as measured by ω_i^c estimates. The results are reported in Figure 6. Panel (a) shows the average wedge estimates across the five firm-size quintiles, where the quintiles are calculated within each industry. The results suggest that the distortionary effects of the GDPR are highest for the smallest firms (28.6%), with monotonically decreasing effects as the firm size gets bigger. This finding is consistent with other evidence on the effects of the GDPR in the literature (Campbell et al., 2015; Koski and Valmari, 2020; Goldberg et al., 2023) and

[48] This sector-level heterogeneity implies additional welfare effects through general equilibrium channels, since sectoral outputs in the economy are likely to be combined in a complementary fashion.

[49] Around 15% of our wedge estimates are negative, which we attribute to noise in the estimation, as the standard errors of average wedges in Figure 5 are quite large. We do not impose a non-negativity constraint on wedges because doing so would implicitly assume positive GDPR costs by construction. Moreover, some firms may face zero or negative wedges if the GDPR eliminates wasteful data practices. We similarly do not impose an upper bound, as values above one, while uncommon, are theoretically possible. The presence of a small share of negative wedge estimates also serves as a useful validation check.

Figure 6: Wedge Heterogeneity by Firm Size and Compute-Augmenting Productivity



(a) Average Wedge by Firm Size

(b) Average Wedge by ω_i^c

Notes: Figure presents our estimation results for the wedge induced by the GDPR (λ_i), averaging across firms within each of the given groups. Panel (a) shows these estimates across the five firm-size quintiles, while Panel (b) shows these estimates across the five compute-augmenting productivity (ω_i^c) quintiles computed using pre-GDPR estimates. Solid lines denote the 95% confidence intervals, and standard errors are calculated using 250 bootstrap repetitions at the firm level.

may reflect the fact that larger firms have better resources to comply with the GDPR.[50]

In panel (b), we report the wedge distribution across quantiles of the compute-augmenting productivity distribution. As firms become more compute-intensive, the magnitude of the wedge decreases monotonically from 28.6% in the first quantile to 18.5% in the last quantile.

6.3 The Effect of the GDPR on the Cost of Information

How do the additional data costs resulting from the GDPR affect firms' variable production costs? To answer this question, we begin by deriving the effects of wedges on the "cost of information", the cost of producing a given level of information. This cost function can be derived from the CES production function as follows:

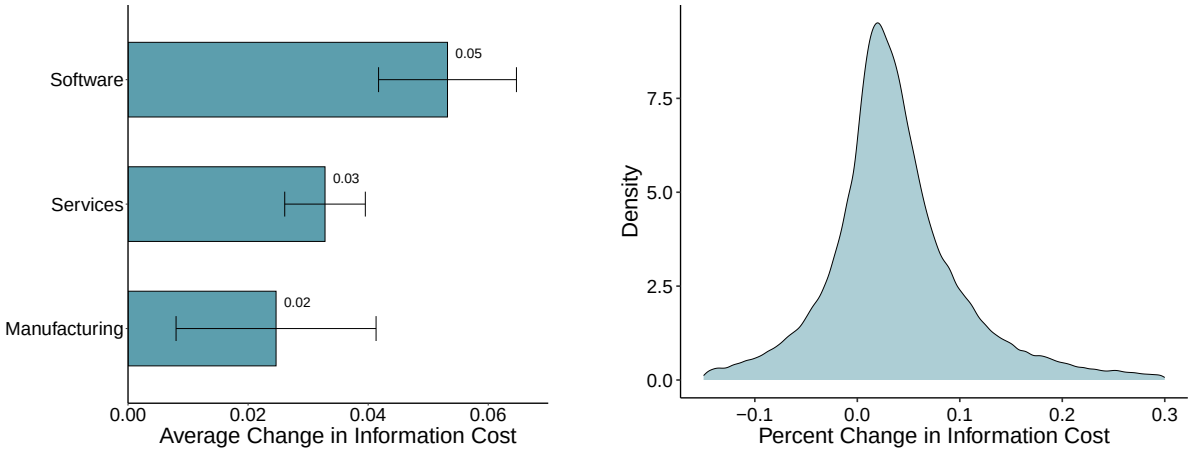
$$CI^*(I_{it}, p_{it}, \lambda_i) = I_{it}\left((\omega_{it}^c)^\sigma \left(p_{it}^c\right)^{1-\sigma} + \alpha^\sigma \left((1+\lambda_i)p_{it}^d\right)^{1-\sigma}\right)^{1/(1-\sigma)}, \tag{11}$$

with the derivation provided in Appendix F.4. This equation shows that the impact of λ_i on the information cost increases with data intensity (α), and decreases with the elasticity of substitution (σ).

We use Equation (11) to estimate the percentage increase in the cost of information post-GDPR by considering two scenarios: (i) a case in which there was no wedge ($\lambda_i = 0$), so the cost of data is p_{it}^d, and (ii) the realized case in which the cost for firms included the

[50]This heterogeneity analysis is also potentially informative about the impact of the GDPR on multinational firms that we exclude from our main analysis. Since multinational firms tend to be large, the likely effects on them are smaller than the average effect we report in the paper.

Figure 7: Percent Increases in Information Costs



(a) Avg. Change in Info. Cost by Industry **(b)** Distribution of Changes in Information Cost

Notes: Figure presents the estimates of the percentage change in the cost of information induced by the GDPR calculated using Equation (11). Panel (a) presents the average estimated percentage increase in the cost of information for firms within each industry. Solid lines denote the 95% confidence intervals, and standard errors are calculated using 250 bootstrap repetitions at the firm level. Panel (b) presents the full distribution of the estimated percentage increase in the cost of information.

costs of regulations: $(1 + \lambda_i)p_{it}^d$.[51] Using our estimates of model parameters, we calculate the ratio of (ii) to (i) for every firm-month at the estimated parameters (as prices and ω_{it}^c change month to month). This calculates the percentage change in information cost, which we further average to obtain firm-level measures.

The results for the percentage increases in information costs are reported in Figure 7. Panel (a) shows the average change by industry, plotting the mean along with the 95% confidence intervals. The average increase in the variable cost of information is 3.90%, and varies across industries, ranging from 2.47% in manufacturing to 5.32% in software. In addition to this industry-level heterogeneity, Panel (b) shows substantial firm-level heterogeneity.

To put these results in perspective, it is useful to compare them to the estimates in Bloom et al. (2012), which study the productivity of IT inputs in US multinational firms relative to EU firms. Their main result is that US multinationals generate approximately 1.7 pp more revenue from IT than domestic and multinational EU firms. This comparison suggests that our estimates are economically important. It also suggests that, by focusing

[51] Note that we can calculate the percentage increase in the cost for a given information level I, without taking into account the effects of changing I on information costs. The level of I would affect the unit cost of information when the information production function exhibits increasing or decreasing returns to scale. See Equation (23) in Appendix F.4 for more information.

only on domestic firms, we may miss some IT-related productivity effects in multinational firms, but these are unlikely to be large relative to our estimates, given the magnitudes reported in Bloom et al. (2012).

Why does an average of 22.4% increase in the cost of data reported in the previous section lead to only a 3.9% average increase in the information cost? To analyze this, we decompose the effects of λ_i on information cost as follows:

$$\frac{\mathrm{d}CI^*_{it}}{\mathrm{d}\lambda_i}\frac{\lambda_i}{CI^*_{it}} = \underbrace{s^d_{it}\,\lambda_i}_{\text{direct effect (+)}} + \underbrace{\left[s^d_{it}\left(\frac{\partial D^*_{it}}{\partial \lambda_i}\frac{\lambda_i}{D^*_{it}}\right) + \left(1-s^d_{it}\right)\left(\frac{\partial C^*_{it}}{\partial \lambda_i}\frac{\lambda_i}{C^*_{it}}\right)\right]}_{\text{firm re-adjustment margin (-)}},$$

where s^d_{it} denotes the cost share of data in information production. In this decomposition, the first term—the direct effect—represents the increase in costs if firms do not re-optimize their data-compute input mix, while the second term—the firm re-adjustment margin—is the extent to which firms can mitigate the increase in costs by substituting data for compute while holding production fixed. Conceptually, if firms do not re-optimize their inputs, the increase in the cost of information would be determined by the expenditure share of data in information (s^d_{it}) multiplied by the wedge (hence the positive direct effect). However, firms' input re-optimization would reduce this effect depending on the elasticity of substitution (hence the negative re-adjustment margin).

Both channels explain why the cost of information increase is about a fifth of the average wedge. First, we find that the average direct effect is small at 4.20% because data expenditures account for only 23.0% of information production costs. The small expenditure share of data is an equilibrium outcome determined by both the data's role in the production function and its price relative to the compute. This observation—that firms allocate substantially more resources to computation than to data—provides an important insight into the role of data and computation in firm production.

Looking at the re-adjustment margin, we find that given the strong complementarity of data and compute, firms are limited in their ability to mitigate the increase in the information cost by substituting data for compute. Therefore, the average firm re-adjustment margin is only −0.29% (see Figure OA-5(b) for the distribution), contributing minimally to the overall effect of the GDPR on the cost of information.

To summarize, the small increase in the cost of information primarily comes from the small expenditure share of data in information production, with the re-optimization margin having little impact. Overall, this section highlights the importance of understanding the firm production with data to quantify the cost of privacy regulations.

Table 7: Effects of the GDPR on Production Costs by Industry

	Software (1)	Services (2)	Manufacturing (3)
	Panel A. Key Parameter Values		
Increase in Information Costs (ΔCI_i)			
Mean increase	5.32%	3.28%	2.47%
95% CI	[4.17% - 6.47%]	[2.61% - 3.95%]	[0.80% - 4.13%]
Elasticity of Substitution ($\bar{\sigma}$)			
Lashkari et al. (2023)	0.83	0.18	0.17
Information Expenditure Share (s_i^I)			
Median share	11.8%	5.0%	3.1%
Range of estimates	7.1% - 24.7%	2.9% - 6.7%	2.3% - 4.1%
	Panel B. Estimation Results		
Increase in Production Costs (ΔVC_i)			
Mean increase	0.62%	0.16%	0.08%
Range of estimates	[0.29% - 1.57%]	[0.08% - 0.26%]	[0.02% - 0.17%]

Notes: This table presents estimates of Equation (13) calibrated with increases in the cost of information estimated in Section 6.3 and information expenditure shares estimated from Aberdeen and other industry surveys for each industry. The mean increase in production costs is calculated with the mean increase in information costs and the median information expenditure share. The range of estimates is calculated by combining the 5^{th} - 95^{th} percentile increases in information costs with the lower and upper range of information expenditure share estimates, respectively. Columns (1), (2), and (3) show estimates for software firms (SIC 7370-7377), services firms, and manufacturing firms, respectively. Appendix H provides more detail about the information expenditure share estimates, the point estimates of $\bar{\sigma}$ taken from Lashkari et al. (2024).

6.4 The Effect of the GDPR on Firm Production Costs

Up until now, we have limited the scope of our analysis to the firm's production of information. In this subsection, we sacrifice some generality to analyze how changes in information costs translate into changes in production costs using simple back-of-the-envelope calculations under additional assumptions.

We follow Lashkari et al. (2024) by using a nested CES production technology, where information I is combined with non-information inputs such as capital and labor, $M(L, K)$. We denote the production function by:

$$Y_i = v_i\left(\beta I_i^{\bar{\rho}} + (1-\beta)M_i^{\bar{\rho}}\right)^{1/\bar{\rho}}, \tag{12}$$

where v_i denotes firm productivity, β denotes information intensity in production, and $\bar{\sigma} = 1/(1-\bar{\rho})$ represents the elasticity of substitution between information and non-information inputs. We drop the time subscript since we conduct this analysis cross-sectionally.

We show in Appendix H.1 that under some simplifying assumptions—that all inputs are flexible, firms are price takers in the input market, and that firms do not have market power—we can derive how information cost changes translate into production costs by using sufficient statistics. More explicitly, the expenditure share of information in total production cost (s_i^I) and elasticity of substitution between information and non-information inputs ($\bar{\sigma}$) are sufficient statistics for the effect of the GDPR on production costs:

$$\Delta VC_i = \left((1 + \Delta CI_i)^{1-\bar{\sigma}} \cdot s_i^I + 1 - s_i^I\right)^{1/(1-\bar{\sigma})} - 1, \tag{13}$$

where ΔVC_i denotes the percentage increase in variable production costs due to the percentage increase in the cost of information (ΔCI_i). Equation (13) reveals intuitive comparative statics: a given increase in (ΔCI_i) translates into larger increases in production costs for larger information shares (s_i^I) and lower elasticities ($\bar{\sigma}$).

Now, we turn towards estimating ΔVC_i. We note that we previously calculated ΔCI_i at the firm level in Section 6.3. We will use its mean value as the baseline estimate in this section and its 95% confidence interval to establish bounds. The remaining parameters in Equation (13) are the elasticity of substitution between information and non-information inputs ($\bar{\sigma}$) and the information expenditure shares s_i^I. For the elasticity of substitution, we rely on the estimates by Lashkari et al. (2024), who estimated the elasticity of substitution between IT and non-IT input using firm-level data in different industries.[52] We follow this approach because the estimation of $\bar{\sigma}$ requires information on non-IT inputs, which we do not observe fully. The Lashkari et al. (2024) estimates, reported in Table 7, suggest that information and non-information inputs are complements in all industries.

For the information expenditure shares s_i^I, the estimates are difficult to calculate directly at the firm level, because while we observe firms' cloud expenditures, we do not have reliable data on revenues and costs at the firm level.[53] Instead, we calculate revenue shares at the industry level by using the Aberdeen dataset and various industry-level surveys, which we discuss in detail in Appendix H.2.[54] We use revenue shares rather than cost shares because only revenue information is available in these data sources.

[52] Lashkari et al. (2024) study France from 1995 - 2007. Although their setting predates ours, their comprehensive data on firm-level information technology investment and industry-level parameter estimates provide useful information on production functions with IT and non-IT inputs.

[53] One alternative would be to compute average cloud expenditures at the industry level using our dataset and combine them with industry-level cost measures from publicly available sources such as the US Census. However, this approach would not yield accurate estimates, because the composition of cloud users in our dataset is likely to differ systematically from that of the overall firm population reported in administrative datasets.

[54] While these sources only partially capture the information expenditure share and capture different samples of firms, we aim to provide a range of plausible values by combining estimates across surveys and years.

Under the assumptions of perfect competition and constant returns to scale, the two measures are equivalent. We provide additional discussion on these assumptions and present robustness checks in Appendix H.2 using additional data.

Table 7 reports the median and interquartile range of information revenue share estimates, whereas Table OA-11 reports the estimates from each source separately. We find that the median information expenditure share is highest in software at 11.8%, followed by 5.0% in services and 3.1% in manufacturing. Overall, although each source may have distinct limitations, the resulting estimates are consistent across sources.

We present the estimated ranges for ΔVC_i from Equation (13) in Panel B of Table 7. We estimate that production costs increase by 0.62% for software firms due to the GDPR. These increases are significantly larger than corresponding increases in the services and manufacturing industry, which we estimate as 0.16% and 0.08%, respectively. This difference is primarily driven by the larger information expenditure shares of software firms. This difference is compounded by the fact that software firms also face the largest average wedges and resulting increases in the cost of information.

To provide a sense of the quantitative magnitudes associated with our estimated increases in production costs, we multiply our estimates (ΔVC_i) by the amount of GDP accounted for by each industry in the Euro Area in 2018.[55] This exercise implies an annual variable production cost increase for the software industry on the order of €4.0 billion. Furthermore, although service and manufacturing industries experienced smaller relative increases in production costs, the importance of these industries implies associated annual GDPR costs on the order of €12.5 and €1.6 billion, respectively.[56]

Although these calculations rely on strong assumptions, we view these results as informative in showing how the economic costs estimated from our production function translate into aggregate production costs across different industries. However, we note that our calculations capture only a specific type of cost—namely, the variable cost of using data in production. As a result, they do not account for other direct costs, such as fixed compliance costs or the regulatory uncertainty faced by firms. They also abstract from potential indirect effects, including impacts on innovation through reduced startup formation (Jia et al., 2021) and R&D activity (Blind et al., 2022), as well as broader general equilibrium effects such as misallocation (Hsieh and Klenow, 2009) and aggregate

[55] Our estimates of the GDP accounted by each industry (and their share of the GDP) are €639 billion (5.06%), €7.84 trillion (73.4%), and €1.95 trillion (16.9%) for software, services, and manufacturing, respectively. We discuss how we attribute GDP to industries in greater detail in Appendix H.2.

[56] These numbers are in the same ballpark as some of the available estimates from surveys. For example, Ernst & Young estimated that in 2018, the largest 500 corporations in the world were on track to spend a total of $7.8 billion to comply with the GDPR (Bloomberg Businessweek, 2018).

responses (Lashkari et al., 2024).

7 Conclusions

In this paper, we examine the impact of the GDPR on firm data input choices and their production costs. Comparing EU firms affected by the GDPR to similar firms in the US, we document that firms stored 25.7% less data and did 15.4% less computation two years after the GDPR, becoming less data-intensive. To map the observed shifts in input choices to changes in firms' production costs, we also propose a production function in which firms aggregate data and computation through a CES functional form. Estimates of this production function suggest that data and computation are strong complements in production. We then model the cost of the GDPR as a wedge between the marginal product of data and its price and find that the GDPR drove an average increase in the variable cost of data of 22.4%, with small firms experiencing more significant cost increases.

Using our estimates of production model parameters, we find that these increases in data costs translate into an average increase of only 3.9% in the variable costs of "information." This relatively modest effect, despite an average 22.4% increase in data input costs, stems primarily from data's smaller expenditure share in firm production relative to computation. Finally, by assuming that the firm production takes a nested-CES form in information and other inputs, we estimate that these wedges imply a 0.08% increase in production costs for manufacturing firms and substantially larger increases around 0.62% for more data-intensive software firms.

Our results contribute to the literature on the costs of the GDPR by focusing on data inputs in firm production that have rarely been studied. In doing so, they complement existing work and highlight the importance of analyzing privacy regulation through a multidimensional view of data usage, jointly considering data and computation as inputs into firm production.

We leave several important margins for future research, including studying the fixed costs of compliance and multinational firms. We reiterate, however, that this paper is only a partial analysis of the welfare effects of the GDPR, as we are completely agnostic to the benefits that consumers derive from privacy protections. A full welfare analysis must incorporate these benefits into a single estimation framework.

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Data, Privacy Laws & Firm Production: Evidence from GDPR

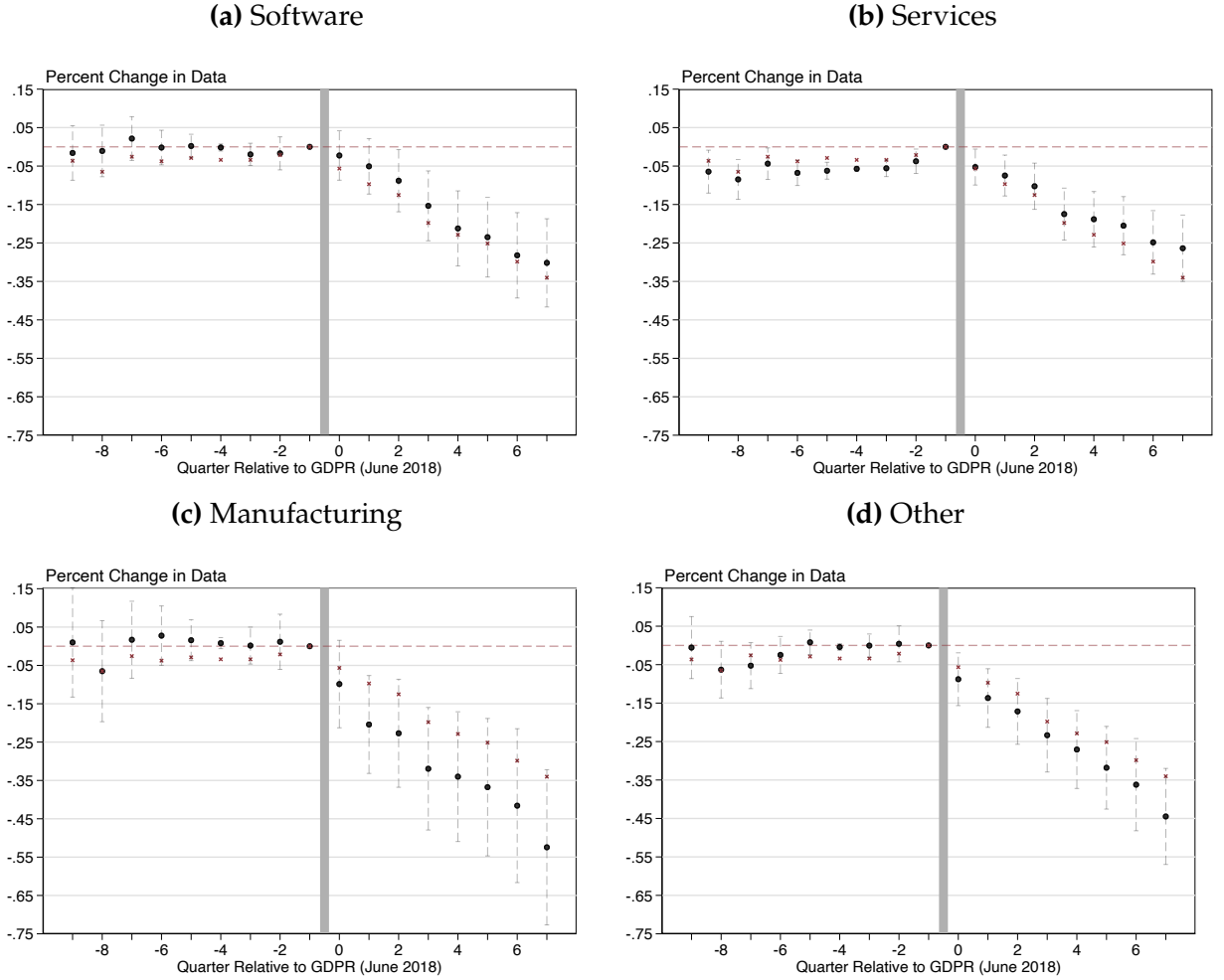
Mert Demirer, Diego Jiménez-Hernández, Dean Li and Sida Peng

Appendix - For Online Publication

Contents

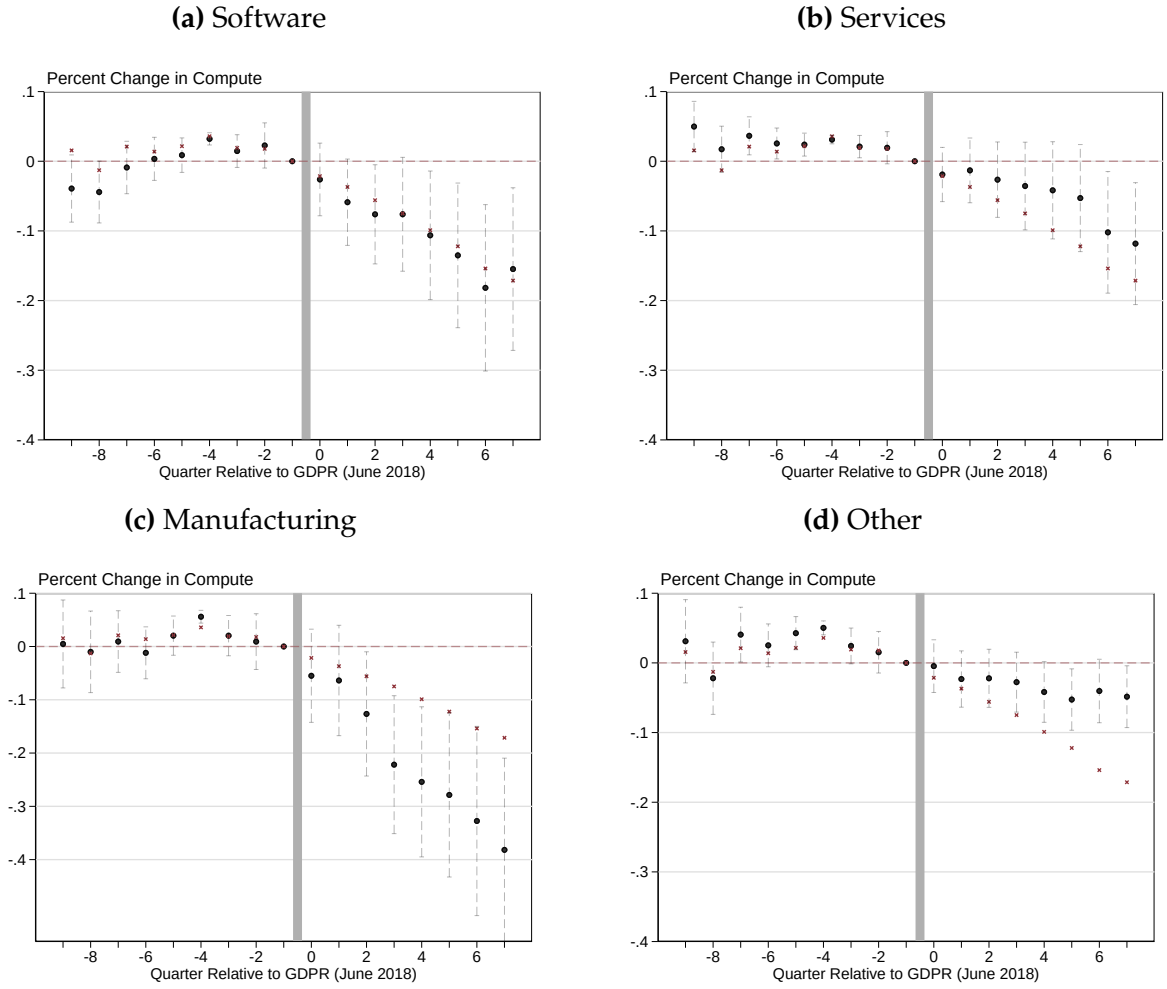
A Additional Exhibits

Figure OA-1: Event Study Estimates of the Effect of the GDPR on Cloud Inputs (Effects on Storage by Industry)



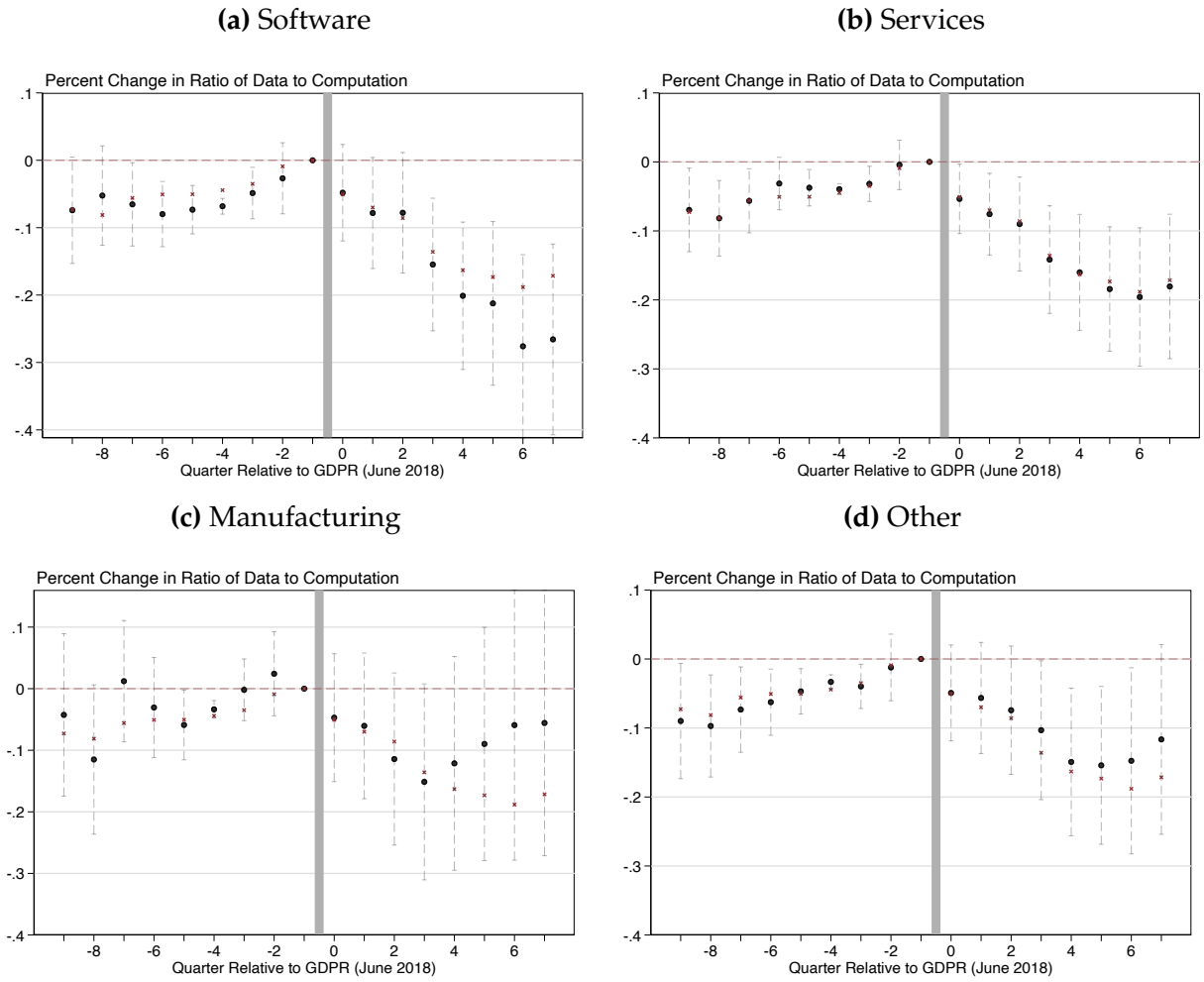
Notes: Figure presents estimates of equation (1) of β_q, the coefficient on the quarter of the move interacted with our treatment indicator, when the outcome is log storage. The coefficient in the quarter before the GDPR's implementation is normalized to zero. Dashed bars represent the 95 percent confidence intervals, and standard errors are clustered at the firm level. Results are broken down by industry, and red dots show the main estimates from the paper. The full definition of industries and the corresponding observation numbers are available in Table 4.

Figure OA-2: Event Study Estimates of the Effect of the GDPR on Cloud Inputs (Effects on Compute by Industry)



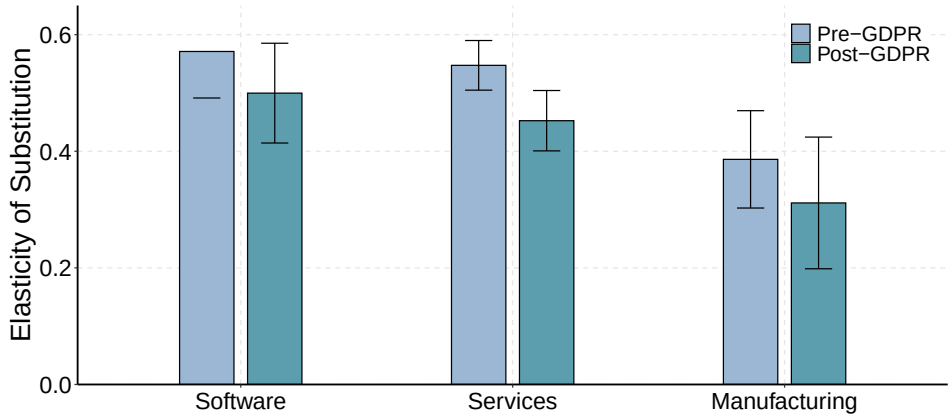
Notes: Figure presents estimates of equation (1) of β_q, the coefficient on the quarter of the move interacted with our treatment indicator, when the outcome is log computation. The coefficient in the quarter before the GDPR's implementation is normalized to zero. Dashed bars represent the 95 percent confidence intervals, and standard errors are clustered at the firm level. Results are broken down by industry, and red dots show the main estimates from the paper. The full definition of industries and the corresponding observation numbers are available in Table 4.

Figure OA-3: Event Study Estimates of the Effect of the GDPR on Cloud Inputs (Effects on Data Intensity by Industry)



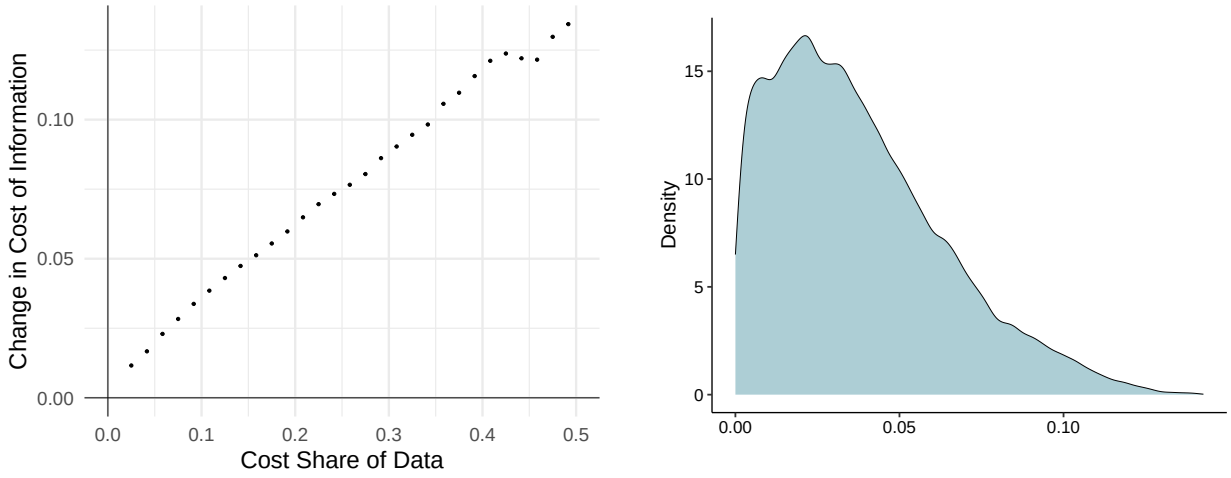
Notes: Figure presents estimates of equation (1) of β_q, the coefficient on the quarter of the move interacted with our treatment indicator, when the outcome is log data intensity. The coefficient in the quarter before the GDPR's implementation is normalized to zero. Dashed bars represent the 95 percent confidence intervals, and standard errors are clustered at the firm level. Results are broken down by industry, and red dots show the main estimates from the paper. The full definition of industries and the corresponding observation numbers are available in Table 4.

Figure OA-4: Elasticity of Substitution Between Data and Compute for US Firms



Notes: This figure presents our estimation results of the elasticity of substitution between data and compute (σ) across industries. We present separate estimates for the pre- and post-GDPR (σ_1 and σ_2, respectively). Standard errors are calculated using 250 bootstrap repetitions.

Figure OA-5: Additional Results on Information Cost

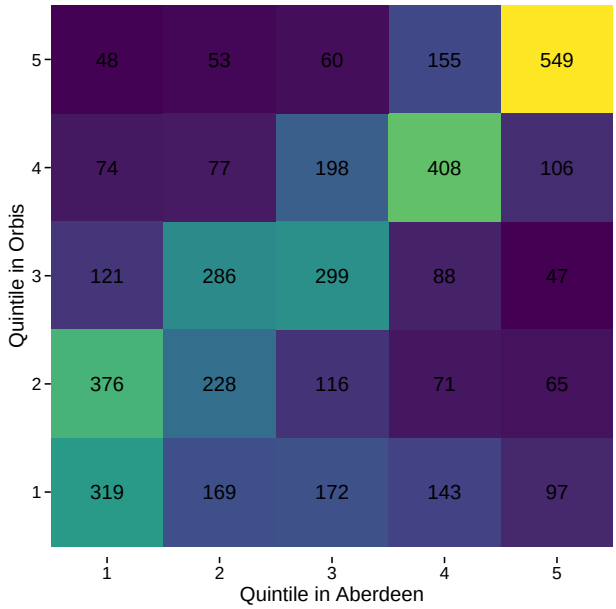


(a) Avg. Change in Info. Cost by Data Share

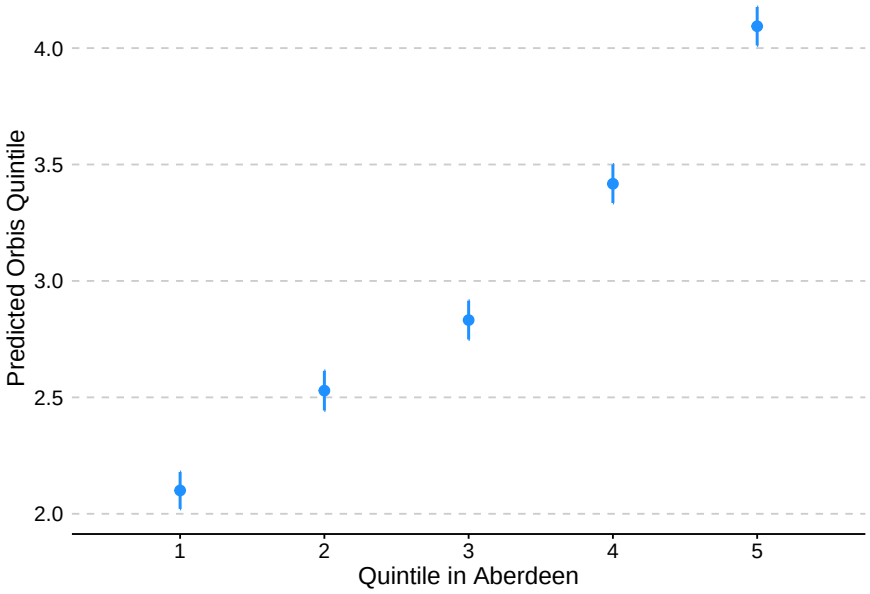
(b) Firm Re-Adjustment Margin

Notes: Figure presents our additional estimation results for the change in the cost of information induced by the GDPR. Panel (a) presents the average estimated increase in the cost of information by the pre-GDPR share of data expenditures in information production costs. Panel (b) shows our estimates of the "firm re-adjustment" contribution to the total change in the cost of information, computed firm by firm as the difference between the increase in the cost of information and the first-order approximation given by the data expenditure share times the wedge.

Figure OA-6: Correlation of Employment Quintiles: Aberdeen vs. Orbis



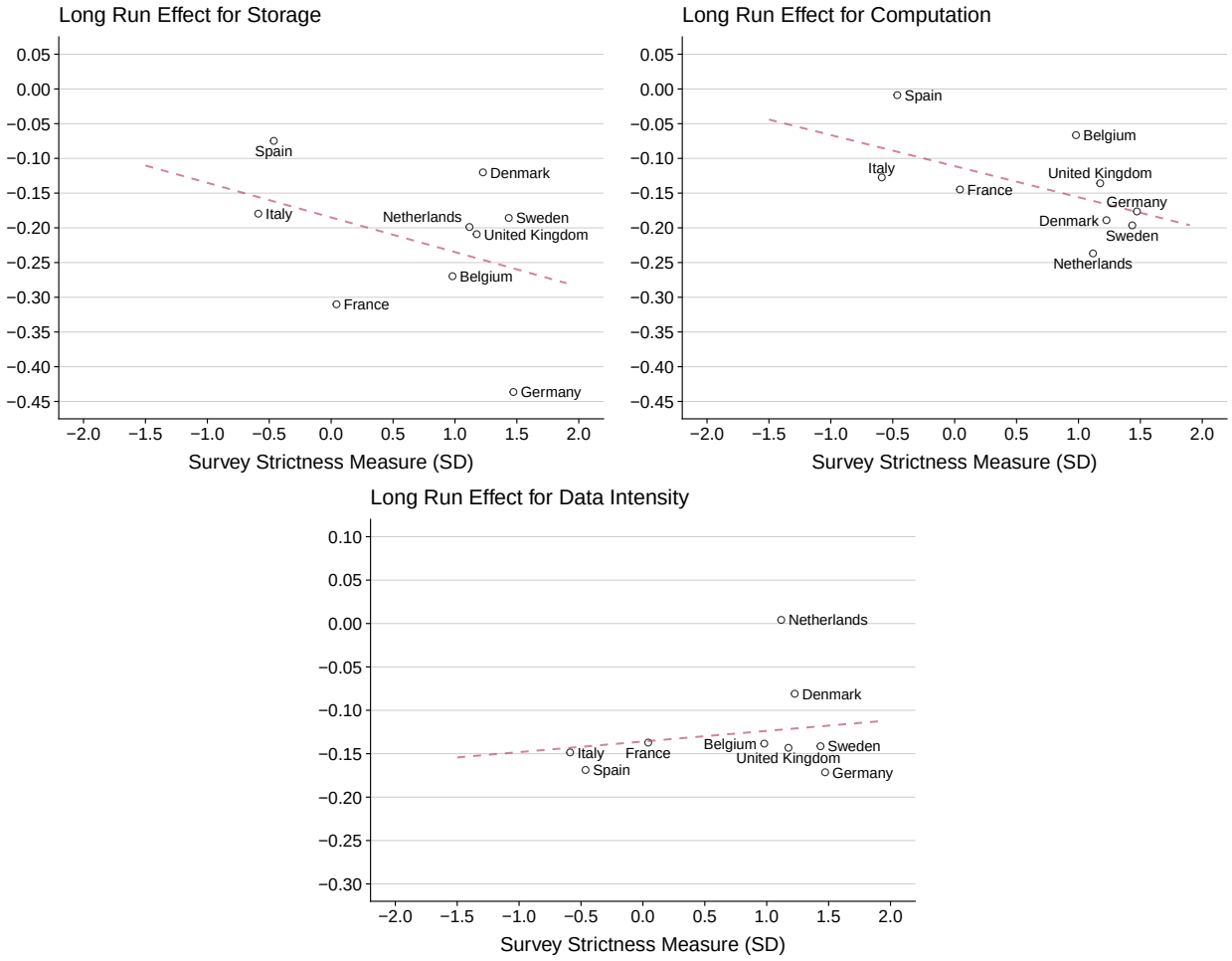
(a) Correlation Heatmap



(b) Quintile Prediction

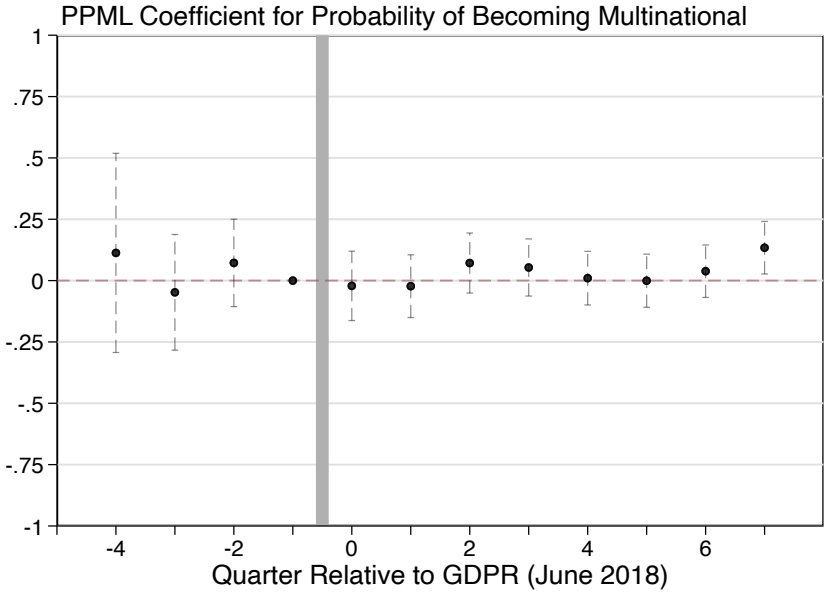
Notes: This figure shows the correlation between employment quintiles from Aberdeen (Dun & Bradstreet) and Orbis data for firms present in both datasets. Panel (a) presents the correlation heatmap between quintiles. Panel (b) presents the predicted Orbis quintile based on Aberdeen data.

Figure OA-7: Regulatory Stringency vs. GDPR Effects by Country



Notes: This figure shows the relationship between regulatory stringency and the estimated effect of the GDPR across EU countries, where δ_2 in equation (2) is modified to allow for country-specific coefficients. For confidentiality, the plot is limited to the nine EU countries with the largest representation in our sample. The red dashed line denotes the weighted line of best fit.

Figure OA-8: Transition to Multinational Status After GDPR



Notes: Figure reports event-study estimates of the effect of the GDPR on the probability that EU firms become multinationals relative to U.S. firms. This modifies equation (1) so that the outcome $\log(Y_{it})$ is instead a binary indicator of whether a firm is "multinational" in that quarter. The sample comprises firms that stored data exclusively in either the European Union or the United States prior to the year preceding the GDPR, excluding trial usage below 1 MB or 0.1 percent of firm storage. Firms are classified as "multinational" if they store data in multiple geographic regions, with particular attention to storage across the EU and the US. Estimates are obtained from a Poisson pseudo–maximum likelihood event-study specification controlling for firms' pre-GDPR cloud usage and industry. The coefficient corresponding to the quarter immediately prior to the GDPR's implementation is normalized to zero. Dashed bars indicate 95 percent confidence intervals, and standard errors are clustered at the firm level.

B The Impact of the GDPR on Firms

B.1 GDPR Summary

In this section, we present a more detailed description of the GDPR. In particular, we focus on the main changes that firms must implement to comply with the GDPR. This section is compiled from information presented in IT Governance Privacy Team (2017), Dibble (2019), Voigt and Von dem Bussche (2017), O'Kane (2017) and original GDPR legal text.

Definition of Controller and Processor (Article 4). A controller is defined as an entity that determines the purposes and means of processing personal data. A processor, on the other hand, is defined as an entity that processes personal data on behalf of a controller. Under the GDPR, a processor is not considered a third party; therefore, the controller may engage a processor at its discretion and does not require a legal basis to do so. If a processor is chosen, it must be suitable and provide sufficient guarantees to implement appropriate technical and organizational measures that meet GDPR requirements and protect data subjects' rights. Both parties must enter into a written contract or other legal agreement to bind the processor to the necessary conditions.

Records of Processing Activities (Article 30). Controllers and processors must create records of their processing activities that include details on the purposes of processing, the categories of data being processed, and descriptions of the technical and organizational security measures in place. There are exceptions to record-keeping requirements for organizations with fewer than 250 employees unless the processing it carries out is likely to result in a risk to the rights and freedoms of data subjects, the processing is not occasional, or the processing includes special categories of data.

Designation of a Data Protection Officer (Article 37). The GDPR requires data controllers and processors to designate a Data Protection Officer (DPO) in the following cases: (i) the processing is carried out by a public authority or body, except for courts acting in their judicial capacity; (ii) the core activities of the controller or the processor involve regular and systematic monitoring of data subjects on a large scale; (iii) the core activities of the controller or the processor consist of processing on a large scale of special categories of data listed in Article 9 and Article 10.

Preparing a Data Protection Impact Assessment (Article 35). If an intended processing activity, especially one involving new technologies, is likely to result in a high risk to the rights and freedoms of data subjects, then firms must conduct a Data Protection Impact Assessment (PIA) to identify and implement appropriate measures to mitigate privacy

risks. The PIA should be conducted at the start of a project so that all stakeholders are aware of any potential privacy risks. The PIA should include the following components: (i) a systematic description of the purposes and planned processing operations, including the controller's legitimate interests (if applicable); (ii) an assessment of the necessity and proportionality of the processing in relation to the purpose; (iii) an assessment of the risks to the rights and freedoms of the data subjects; and (iv) the measures planned to address these risks.

Technical and Organizational Measures for Data Security (Article 32). The controllers must put technical and organizational measures in place to protect personal data. They should implement appropriate data protection policies that are proportionate to their processing activities with a risk-based approach. The GDPR does not specify a specific set of security controls that firms must implement but rather encourages data controllers and processors to implement "appropriate" controls based on risk.

Data Subject Rights (Article 14-21). Under the GDPR, individuals have extensive rights when their personal data is collected by data controllers. These rights include requesting data erasure, data transfer, and data access. If a request is made by a data subject, the firm must respond to the request without undue delay and generally within one month of receiving the request. As a result, firms may need to proactively fulfill a number of obligations so that they can quickly provide information about their processing, erase personal data, provide or transfer specific data, or correct incomplete personal data.

Data Breach Notification (Article 33). Under the GDPR, controllers have a general duty to report personal data breaches to supervisory authorities within 72 hours of becoming aware of them. When a personal data breach is likely to result in a high risk to the rights and freedoms of natural persons, the controller must notify the affected data subjects without undue delay.

Penalties and Increased Liability Risk (Article 83). The GDPR makes it easier for data subjects to bring civil claims against data controllers and processors. The data subject does not need to have suffered financial loss or material damage (e.g., loss or destruction of goods or property) to bring a claim. They can also claim for non-material damage, such as distress or hurt feelings. The GDPR sets out two levels of administrative fines. The higher level of fines can be up to €20 million or 4% of the total global annual turnover of the preceding financial year, whichever is higher. This level applies to infringements of certain fundamental principles, such as individuals' basic rights and freedoms. The lower level of fines can be up to €10 million or 2% of the total global annual turnover of the preceding financial year, whichever is higher. This level applies to other types of infringements.

B.2 The Compliance Cost of the GDPR

Compliance with the GDPR is likely to create significant costs for firms. Some of these costs are one-time fixed costs associated with actions required for initial GDPR compliance, while others are ongoing variable costs required for ongoing compliance. In this section, we present evidence highlighting the impact of the GDPR on firm costs collected from various firm surveys. See Chander et al. (2021) for an overview of the costs of compliance associated with data privacy laws for businesses.

Although no official statistics are available on the overall costs of the GDPR, surveys provide information on the costs of compliance with GDPR regulations. The estimates range from an average of $3 million (Hughes and Saverice-Rohan, 2018) and $5.5 million (Ponemon Institute, 2017) to $13.2 million (Ponemon Institute, 2019) and $70 million for the largest firms (Accenture, 2018), depending on the composition of surveyed firms. Importantly, survey responses indicate that these costs are not one-time and that firms expect to incur them repeatedly (Ponemon Institute, 2019). Studies that provide a breakdown of these costs indicate that a substantial share (between one-fifth and one-half) consists of labor costs for privacy compliance personnel. Depending on the study, technology accounts for 12 to 17% of total GDPR cost, and outside consultants and lawyers account for another 19 to 24% (Ponemon Institute, 2019; Hughes and Saverice-Rohan, 2019).

B.2.1 Fixed and Sunk Costs

Operational Changes for Data Security and Processing The GDPR may require numerous operational changes for firms, including the implementation of data protection management systems. These changes involve sunk and fixed costs. The cost component associated with operational changes can be substantial, regardless of a firm's data volume. This is because firms must develop and implement technical and organizational measures to comply with potential consumer requests and other data breach reporting requirements. Other components of fixed costs include data mapping, writing privacy notices, and training employees on GDPR compliance.

Data Protection Officer The GDPR requires a data protection officer (DPO) for certain organizations, depending on their data processing activities. Although DPO is primarily a fixed cost, it can also be viewed as a variable cost, as the number of employed DPOs may increase with firm size and data volume. A survey by IAPP of 370 respondents suggests that 18% of firms have appointed multiple DPOs (Hughes and Saverice-Rohan, 2017), indicating that DPOs could be a variable cost for large firms.

B.2.2 Variable Costs

Some costs associated with GDPR compliance are variable and scale with the organization's size and the volume of data it holds. According to a survey conducted by DataGrail, 88% of firms spend over $1 million, and 12% spend more than $10 million annually to maintain GDPR compliance (DataGrail, 2020). The heterogeneity in continuous compliance costs suggests that some costs are variable and change with firm size and the amount of stored data. Below, we provide some examples of variable GDPR compliance costs.

Handling Customer Requests Under the GDPR, consumers have the right to have their data erased, transferred, or made available for download. The costs of handling these requests are likely to be variable, as companies with more data are more likely to receive requests. Survey evidence supports this conclusion. According to (DataGrail, 2020), 58% of companies receive more than 11 customer requests per month, and 28% receive more than 100 requests. More than half of companies have at least 26 employees managing these requests. Moreover, only 1% of companies report having fully automated these requests, whereas 64% handle them entirely manually.

Recording Data Processing Activities An important aspect of the GDPR is the requirement to develop a plan for new projects that involve data collection and processing. For example, if a firm needs to implement a new machine learning algorithm that incorporates new variables, it must conduct a detailed risk assessment, cost-benefit analysis, and identify safeguards to prevent potential future issues. This constitutes a significant project-specific cost that might affect the cost-benefit trade-off for implementing new data collection projects. Therefore, some data-intensive projects may not be implemented due to the additional cost.

Improved Data Security Keeping data in a more secure environment can also increase the variable cost of data, especially for cloud computing users. Cloud providers offer different tiers of security for their storage services, with higher levels of security typically corresponding to higher costs. Purchasing these additional storage services due to the GDPR would increase the marginal cost of storing data for firms.

Liabilities The maximum penalties under the GDPR include fines of up to €20 million or 4% of the company's global annual revenue, whichever is greater. However, the actual penalty amount is determined by the nature and severity of the violation and is likely to increase with the amount of data stored by the firm. Moreover, one can imagine that the probability of a cyberattack increases with the volume of data. Another related variable cost is cybersecurity insurance. Of the 1,263 organizations surveyed in Ponemon Institute

(2019), 31% of respondents purchased cyber-risks insurance. Among those insured, 43% had coverage for GDPR fines and penalties.

B.3 Publicly Available GDPR Fine Data

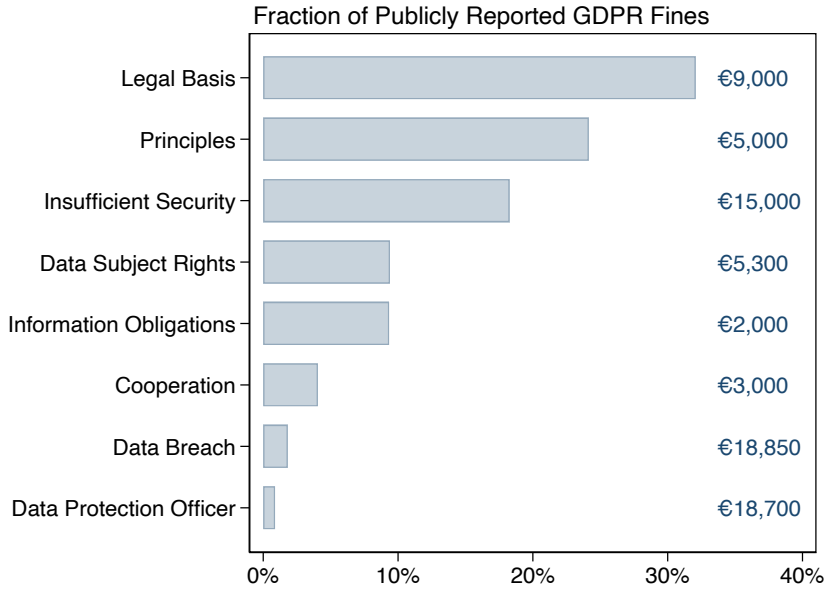
Our primary source of publicly available fine data is a database maintained by CMS Legal Services, a large international law firm operating in more than 40 countries. This data provides an overview of the public fines and penalties imposed by data protection authorities under the GDPR. Although not all fines are made public, the data on public fines is quite rich, including the fine amount, the entity being fined, the country of the fine, and the GDPR articles under which the fine was leveled.[57] The database contains more than €3 billion in fines levied in the five years after the implementation of the GDPR. Furthermore, the database includes primary and secondary sources for each fine.

For each fine, we scrape the fine amount, the entity it was levied on, the date, and why the fine was levied. In Figure 1 of the paper, we show the distribution of fine sizes, highlighting that there is considerable variation in the size of the fines. There is also substantial variation in the specific reasons that fines were levied, and these reasons fall into eight categories: (a) insufficient legal basis for data processing, (b) insufficient involvement of data protection officer, (c) insufficient technical and organizational measures to ensure information security, (d) insufficient fulfillment of information obligations, (e) non-compliance with general data processing principles, (f) insufficient fulfillment of data subjects rights, (g) insufficient cooperation with the supervisory authority, and (h) insufficient fulfillment of data breach notification obligations. For brevity, we label these as “legal basis", “data protection officer", “data security", “information obligations", “data principles", “data subject rights", “non-cooperation", and “data breach notifications" respectively.

In Figure OA-9, we show the share of fines that were levied under each reason and the median fine size conditional on the reason. Perhaps unsurprisingly, data security concerns lead to the largest fines. The median fines for insufficient information security and insufficient notification of data breaches are €15000 and €18850, respectively, while the median fines for non-cooperation and insufficient fulfillment of information obligations are €3000 and €2000, respectively. Overall, the distribution of reasons cited for publicly available GDPR fines suggests fines may be levied for various reasons.

[57] We scraped this data in May 2023 through https://www.enforcementtracker.com/.

Figure OA-9: Publicly Reported GDPR Fines



Notes: Figure presents the distribution of reasons given for GDPR fines, using the publicly reported fine data described in Appendix B.3. Fine reasons are derived from the GDPR Article quoted in the fine, and these reasons are broken out into eight categories by CMS Law. We drop the 1.5% of fines that have no quoted GDPR article. Appendix B.3 describes these categories in further detail. The median fine size by reason is provided in blue text on the right side of the figure.

B.4 The GDPR's Impact on Manufacturers

One of the more striking findings in the paper concerns the manufacturing sector. In the event study analysis in Section 4, we find that manufacturers exhibit the largest declines in data and computation usage across all industries following the GDPR. At first glance, this result may appear surprising, given the common perception that manufacturing firms are relatively less data-intensive than firms in other industries. Moreover, the production function analysis in Section 5 implies a relatively smaller increase in wedges for manufacturers, seemingly in contrast to the event study results. In this section, we shed light on these results by providing additional background on manufacturing firms' characteristics and production technologies. In particular, we argue that the existing empirical evidence in the literature is consistent with manufacturers being intensive data users, and that the differences between event study and wedge estimates can be explained by the elasticity of substitution and other characteristics of the manufacturers' production functions that we estimated in this paper.

B.4.1 Manufacturers and Data Usage

Contrary to the widespread perception that the manufacturing sector lags behind in data use and digitization, a growing body of evidence indicates that manufacturing firms—at least in the US—are among the leading adopters of data and digitization technologies (Brynjolfsson et al., 2021; Zolas et al., 2021; McElheran and Yang, 2026; McElheran et al., 2025; Forman and McElheran, 2025). Using US Census data, McElheran and Yang (2026) document that 91% of manufacturing firms report using digitized data, and nearly 73% engage in descriptive analytics. Moreover, adoption rates increase sharply with firm size, with larger firms substantially more likely to digitize information and employ analytics (Zolas et al., 2021).

Manufacturing firms are not only heavy users of data in absolute terms but also lead other industries in relative data usage in production. In particular, according to Zolas et al. (2021), the manufacturing industry leads in the adoption of advanced business IT technologies, with about 15% of firms reporting the use of at least one advanced technology, exceeding Health Care (14%), Information (12%), Education (11%), and Professional Services (10%). In a more recent study by McElheran and Yang (2026), manufacturing is characterized as data-intensive relative to sectors commonly viewed as information-heavy, generating roughly twice as much digital information as industries such as media and finance.

Importantly, evidence suggests that some of the data used by manufacturing firms involve personal information. Zolas et al. (2021) document that personnel and financial information are the most commonly digitized data types across all sectors, including manufacturing. Customer feedback and marketing data also rank among the most frequently digitized categories.

We note that these empirical patterns have been documented for only US firms, and we do not have comparable, detailed evidence on data use among EU manufacturers. However, given that our sample consists of cloud-adopting firms, which tend to be larger than the average manufacturing firm (Zolas et al., 2021), it is plausible that adoption rates of data and digitization technologies are also high among EU manufacturing firms in our sample.

B.4.2 Manufacturing Sample

Another important issue related to our identifying assumptions concerns the validity of the comparison between domestic manufacturing firms in the US and the EU. Manufacturing industries in both regions have undergone substantial structural changes in recent

decades—most notably, manufacturing in the US experienced a sharp decline in the 2000s, followed by relative stabilization in the 2010s, while manufacturing in the EU faced increased competitive pressure from Chinese manufacturers. While these developments have affected the overall size and composition of each manufacturing sector, our evidence suggests that domestic manufacturers in our sample follow broadly similar trajectories in their data-related activities. Specifically, the parallel pre-trends reported in Figures OA-1 and OA-2 indicate that manufacturers in the EU and the US exhibit closely aligned short-run trends in data storage and computing usage. These patterns suggest that differential trends across manufacturing sectors in the US and the EU are unlikely to explain our results.

B.4.3 Reconciling the Event Study and Wedge Estimates

Our event study findings in Figure 3 for the manufacturing industry indicate that manufacturers experience the largest declines in both compute usage and data storage, despite facing relatively smaller wedges compared to other industries, as shown in Figure 5. Although the differences between these wedges are not statistically significant, these two seemingly contradictory findings warrant further discussion.

As described in Section 5.3, our identification of wedges comes from production function estimation that exploits firms' responses in the data-to-compute ratio following the GDPR. This ratio is entirely governed by the information production function under cost minimization. By contrast, the event study estimates capture adjustments in input levels that are governed by the firm's overall production technology rather than by the information production function alone. Therefore, understanding the respective roles of the information production function and the firm's overall production function is key to interpreting firms' responses across these two empirical specifications.

Two primary mechanisms can explain why we observe relatively small changes in data intensity in manufacturing (and thus smaller wedges) together with large absolute declines in data and compute usage. The first is the elasticity of substitution between data and compute. As discussed in detail in Section E.2 and illustrated in Figure OA-19, the elasticity of substitution governs how firms adjust the data–to-compute ratio in response to an increase in data costs. When data and compute are close complements, higher data costs reduce both inputs, resulting in only modest changes in the input ratio. By contrast, when the two inputs are close substitutes, an increase in data costs primarily reduces data usage and may even increase compute usage, resulting in larger changes in data intensity.

Given this mechanism, it is informative to examine the estimates of elasticity of substitution across industries. We find that manufacturing exhibits the strongest complementarity

between data and computation among all sectors. This finding aligns with the patterns in data intensity results in Table 4: while manufacturing experiences large level declines in data and compute usage, the corresponding change in data intensity is comparatively modest. Together, these findings support the interpretation that data and computation are more complementary inputs in manufacturing, so increases in data costs reduce both inputs without inducing large shifts in their ratio.

The second explanation concerns the role of data and compute within the broader production function. While the ratio of data to computation is governed by the elasticity of substitution between these inputs, changes in their levels are determined by the overall production technology over all inputs beyond the information aggregate, which we do not explicitly model. To illustrate this point, consider a CES production function with two inputs, information I and a composite input M, and abstract away from the time-varying and firm-specific nature of the information production function due to ω_{it}^{c}:

$$F(I, M) = \left[\alpha I^{\frac{\bar{\sigma}-1}{\bar{\sigma}}} + (1-\alpha) M^{\frac{\bar{\sigma}-1}{\bar{\sigma}}}\right]^{\frac{\bar{\sigma}}{\bar{\sigma}-1}}, \tag{14}$$

where $\bar{\sigma} > 0$ denotes the elasticity of substitution between M and I. The cost-minimizing input demand for information I, holding output fixed, satisfies:

$$\frac{\partial \log I}{\partial \log p_I} \propto -\bar{\sigma}\left(1 - s^I\right) \tag{15}$$

where s^I denotes the cost share of information. This expression implies that, following an increase in the price of information (due to the GDPR wedge), the decline in its level—and thus in the levels of data and computation—is larger when substitution across inputs is easier and when information accounts for a smaller share of total costs. This mechanism provides an explanation for the large declines in data and compute levels observed in manufacturing, as manufacturing industries exhibit the lowest cost share of information among all sectors in Table 7. As a result, even modest changes in wedges can translate into large reductions in both data and computation.

C Data Appendix

C.1 Cloud Computing Details

This section details how firms perform computation and storage in cloud computing, which is the main focus of our paper.

C.1.1 Computation

Firms requiring cloud computation typically opt for virtual machines (VMs). VMs are a type of cloud computing "compute" product that allows users to create and manage servers virtually instead of maintaining their own physical hardware.[58] These VMs run on virtualized infrastructure provided by a cloud computing provider and can access software and computing resources. These machines are typically fully customizable and controlled by the user. Cloud computing VMs can be configured in various ways. Some of the features of VMs that can be customized include memory, storage, networking options, CPU, operating system, and the data center's location. Cloud computing providers offer hundreds of different configurations, and the user chooses the exact configuration when requesting a VM.

In our paper, we use the number of CPU cores in a virtual machine as the key measure of computation outcome because this is the key vertical VM characteristic that determines compute capacity. However, we note that this approach does not consider heterogeneity in other characteristics, such as memory, networking capacity, and VM manufacturer/series.

The unit of observation is "core-hours", which refers to the amount of computing time a VM uses over a given period. The number of core-hours is calculated by multiplying the number of CPU cores by the number of hours the VM runs. For example, if a user runs a VM with 4 CPU cores for 10 hours, the total compute use would be 4 x 10 = 40 core hours. Cloud providers typically use core-hours as the primary measure of VM usage for billing purposes.

C.1.2 Storage

Cloud providers offer a wide range of storage products that can be used for various purposes, including storing and managing data, backing up and recovering data, and archiving data for long-term retention. These products can be categorized into two types: disk storage and database storage. Disk storage provides physical hardware where firms

[58] There are other "compute" products—such as containers and serverless computing—that were also available during our sample period, but they were not extensively used.

can store a wide variety of data, including operating system files, applications, documents, and multimedia files. Disk storage can include different physical configurations, such as Hard Disk Drives (HDDs) and Solid-State Drives (SSDs), as well as Storage Area Networks. Disk storage can also differ based on other characteristics, such as upload and download speed. Databases, on the other hand, are collections of structured data that are hosted and managed in a cloud computing environment by a cloud provider. The differentiation of databases refers to the various types of databases available and their specific features and characteristics, such as MySQL, NoSQL, Oracle, and PostgreSQL.

Firms typically use storage in one of two ways. First, when a firm creates a VM on a cloud provider's infrastructure, it can choose the amount of disk storage it needs and specify the required performance characteristics. They would use this disk storage when computing on that virtual machine. Second, firms might request either disk storage or databases to store and manage application data, and this storage might be used for supporting real-time applications and services or as archiving storage.

Our unit of observation for storage is storage capacity measured in gigabytes (GB). It represents a direct measure of how much data firms store, although it does not measure how storage products may be vertically or horizontally differentiated. An important example of storage differentiation is upload and download speed.

C.2 Sample Selection and Cleaning

In this section, we discuss our sample construction for the event study specification in greater detail. We define a firm as a unique internal identifier for which we are able to observe industry classification and location information. Using this definition, we are able to capture approximately 90% of storage and 95% of computation in our entire sample.

Next, we clean the data by removing outlier observations. To tag a firm as an outlier, we require that we observe the firm's usage in the months immediately preceding and following a given month. We define outliers as large and sudden temporary spikes or dips. These are months in which a firm's usage is either 20 times higher or lower than that of the same firm in the months immediately preceding and following the month. We also filter these by minimum size change to ensure that we are not spuriously removing small firms with more volatile usage. This cleaning removes less than 0.1 percent of observations. We also worked with internal staff to conduct minor cleaning to exclude a small fraction of firms whose observations are affected by the introduction and phase-out of older service models for our provider.

We then construct our sample by conditioning on continuous firm-level observations for one full year, exactly two years before the GDPR. Although the resulting sample of firms

is smaller, conditioning on the continuously observed firms does not significantly change the proportion of the data we observe. In fact, these continuously observed firms are responsible for about 90 percent of storage and computation before the GDPR. We present summary statistics on these sets of firms below in Table OA-1. While for confidentiality, we cannot provide direct comparisons between the number of firms before and after this conditioning, the means of storage and computation are reported relative to a baseline normalization of 1,000 mean units of storage for our baseline sample in Table 2.

Table OA-1: Summary Statistics: Before Conditioning on Observation Period

Industry	Share of Firms	Share Compute	Share Storage	Mean Storage	Mean Compute	Share EU
Software	18.0	20.6	16.6	341	331	58.6
Services	47.1	34.5	38.6	408	296	38.2
Manufacturing	7.7	11.4	10.2	593	518	55.5
Other	27.2	33.6	34.6	651	479	49.7
All	100	100	100	468	345	46.3

Notes: Table presents summary statistics from our matched sample of firms. A description of the sample's construction can be found in Section 3.1, and a more detailed description of the sample construction can be found in Appendix C. This sample presents firms in Cases 1 and 4, as described in Table 1. For confidentiality purposes, we do not report the total number of firms. We also normalize the units of mean storage and mean computation such that everything is presented relative to a mean of 1,000 mean storage units in our baseline sample (Table 2).

C.3 Aberdeen Sample

Aberdeen is a market research firm that gathers data from various sources on firms' hardware and software investments. Every year, they survey a sample of senior IT executives about their software and hardware usage and extrapolate this information to non-surveyed firms. Additionally, they conduct large-scale data collection efforts, such as web scraping job postings and purchasing customer lists from vendors to identify software choices. Our understanding is that information on technology adoption comes only from the latter source. This data also includes sales, the number of employees, industry, and a DUNS number, which are sourced from Dun & Bradstreet. Our sample of Aberdeen data covers the period from 2015 to 2021 at the annual level. The data from Aberdeen has been previously used to study digitization and technology adoption (Graetz and Michaels, 2018; Tuzel and Zhang, 2021).

We use Aberdeen to measure the market shares of cloud providers in the EU and the US. Aberdeen provides information at two levels: the site and enterprise levels. A site

refers to a physical location, while an enterprise corresponds to a firm (which may have multiple sites). The data includes unique site and enterprise IDs and a crosswalk that links the two. On average over sample years, the dataset covers more than 5.9 million sites across the US and EU, and the technology adoption information is reported at the site level. We aggregate site-level information to the enterprise level by assuming that if at least one site within an enterprise uses a technology from a given provider, the enterprise uses that provider's technology.

C.3.1 Match Procedure Between Aberdeen and Cloud Data

Aberdeen's data contains valuable information, such as employment data, that we use to analyze the heterogeneity of our results. However, there is no single identifier we can use to match the anonymous cloud provider's data to Aberdeen, so we must resort to 'non-exact' procedures (also known as fuzzy matching) to link these two datasets. In both the cloud provider's and Aberdeen's data, we observe names, DUNS numbers (with partial coverage in the cloud data), websites (URLs), and partial address information, including postal codes, city, state, and country, for the firms. Additionally, we observe both the subsidiary name and the parent company name in the Aberdeen data, which provides two potential strings to match each observation in our cloud data. Below, we provide details on the matching algorithm.

We use the Jaro-Winkler (JW) distance to match names, which considers the number of transpositions and the number of matching characters between two strings. Intuitively, strings with more characters in common and requiring fewer transpositions for one string to be contained within the other have lower distances. For the same number of character matches and transpositions, the JW distance is smaller for strings that match the first characters of the strings.[59]

For each firm in the cloud computing dataset, we identify the "closest" match in the Aberdeen dataset (using either the parent or subsidiary names). We sequentially match using the following criteria and say that two firms are a match if both:

1. Share the same DUNS number, or
2. Share the same website, or
3. Are in the same postal code, and the name distance is less than 0.1, or
4. Are in the same city, and the name distance is less than 0.08, or

[59] In terms of the implementation, we use the Firm Merge Project (available at https://github.com/microsoft/firm-merge-project) to implement the JW distance in finite time.

5. Are in the same state, and the name distance is less than 0.07, or

6. Are in the same country, and the name distance is less than 0.065, or

7. Are in the same region (e.g., EU), and the name distance is less than 0.045.

Suppose a firm in cloud computing data has multiple matches in the Aberdeen data. In that case, we hierarchize based on the same order as we list our criteria above.[60] Note that we also allow for "looser" string matching when the geographic region in which we search for a given firm is smaller. These cutoffs were selected by visually inspecting the data and balancing the rates of false-positive and false-negative matches.

With this procedure, we are able to match 63% of firms in our baseline sample to Aberdeen firms. We use this matched sample to examine heterogeneity in our results by firm employment size. The change in firm employment over time is less reliable in Aberdeen because employment information does not change for a significant number of firms. For this reason, we use 2018 employment data to define firm size.

C.3.2 Aberdeen Cross-check with Internal Data

Although Aberdeen was widely used to measure IT spending in the 2000s, the data have changed in recent years, broadening its focus from hardware spending to software adoption. While hardware expenditure data primarily relied on surveys, information on technology adoption at a larger scale relies on web scraping, publicly available sources, and extrapolation. This raises the question of how reliable the Aberdeen data is as a source of technology adoption information. We are in a unique position to offer a partial answer to this question because we have internal data from one of the largest cloud providers and can cross-check it against Aberdeen data for this provider.

To implement this, we utilize the matched Aberdeen-internal data sample to investigate whether Aberdeen accurately reports the adoption of our cloud computing provider. In particular, we examine the true positive and true negative rates: (i) the proportion of actual users of our cloud product that are correctly labeled, and (ii) the proportion of users who do not use our cloud product that is correctly labeled. We find that the true positive rate is 64.7 percent, increasing with firm size, and the true negative rate is 62.8 percent, decreasing with firm size. This result suggests that, although the Aberdeen data are not 100% accurate, they still provide a valuable signal regarding cloud adoption.

[60] For example, for a firm in the cloud computing data that we match by criteria (1) and (3) to different firms in the Aberdeen data, we only keep the match in criteria (1), given that DUNS numbers are designed as unique firm identifiers.

D Robustness Checks

This Appendix goes through the most critical threats to identification. We study substitution to other providers in Appendix D.1. We then investigate whether differential price changes (between the EU and the US) may be driving our results in Appendix D.2. We study firms with and without website usage (to measure the extent to which cookie collection drives our results) in Appendix D.3. Finally, we show that our results are robust to alternative choices of empirical strategies, sample selection procedures, and extensive margin/attrition in Appendix D.4.

D.1 Substitution to Other Providers

This section documents that substitution (to other cloud providers or to in-house IT services) is unlikely to drive our results. We provide a battery of exercises, each of which shows that substitution is unlikely to generate the patterns we observe in the data.

Substitution to Other Cloud Providers "Multi-cloud" usage—where firms get cloud services from multiple cloud computing providers—-is common among firms. Industry surveys suggest that over 70% of cloud users are multi-cloud.[61] Multi-cloud usage may be a concern, as we observe data from only one cloud provider, resulting in incomplete cloud usage data. If the GDPR changed the relative attractiveness of our cloud computing provider compared with other providers, perhaps in terms of how readily they accommodated GDPR requirements, then there could have been a differential change in our provider's market share in Europe and the US around the GDPR. This would pose an identification challenge for us.

In particular, we might attribute a decline in cloud storage and computing to firms simply switching their cloud usage to other providers. We note, however, that firms that conduct both storage and computing are likely to do so with the same provider, because data cannot be stored with one provider and processed with another. For example, there are essentially no observations in which a firm uses cloud computing with our provider without also using cloud storage. Thus, our data intensity results should be less affected by any changes in the relative attractiveness of cloud providers.

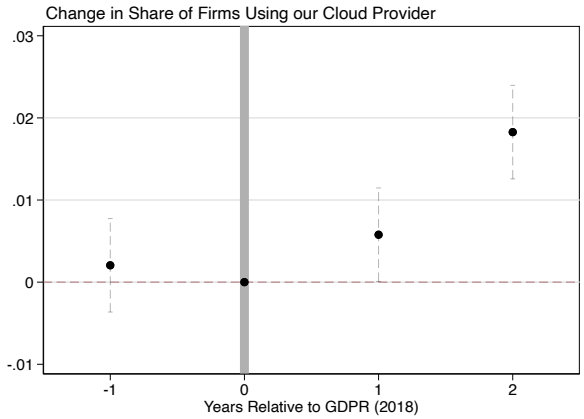
We attempt to address the identification challenge to our storage and computing results with three additional exercises. First, we bring an external dataset, Aberdeen, that provides information on firms' technology adoption and which vendors they get cloud services

[61] See HashiCorp's State of Cloud Strategy Survey reporting that 76% of enterprises have adopted a multi-cloud strategy at HashiCorp State of Cloud Strategy Survey. See also IDC's Cloud Pulse research reporting that 79% of companies use multiple cloud providers at IDC: Ten Trends That Shaped the Cloud Market in 2024.

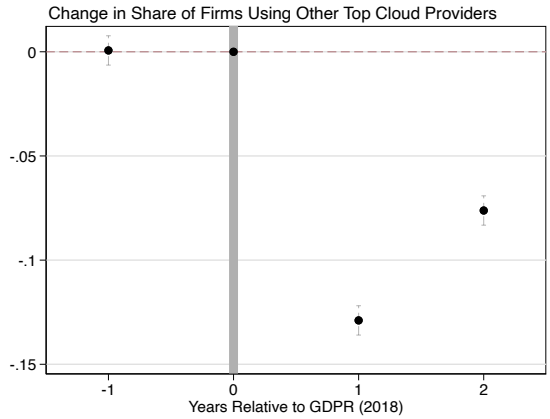
from. Using this dataset, we examine our provider's share of firms and the shares of other top cloud providers in Europe and the US before and after the GDPR, and plot them in Figure OA-10. We find that the share of firms using our cloud provider has increased moderately over time, whereas the share of firms using other cloud providers has decreased. Thus, we do not expect the relative attractiveness of the cloud provider we observe to have decreased following the GDPR.

Figure OA-10: Change in Share of Firms Using Cloud Providers in the EU vs the US

(a) Our Cloud Provider



(b) Other Cloud Providers



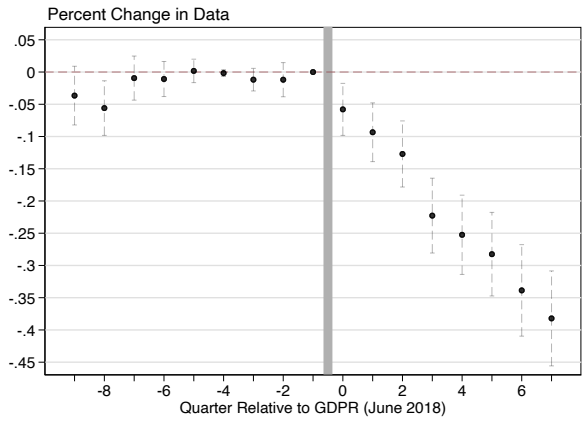
Notes: Figure presents estimates of the difference in the share of firms that use different cloud providers in the EU vs the US. The data source is Aberdeen (formerly known as Harte Hanks). The dependent variable in the left panel is equal to one if a firm uses the cloud provider that we study in this paper. The dependent variable in the right panel is equal to one if a firm uses any of the other cloud providers. The coefficients plot the difference in the share of firms using the given cloud provider in the EU, relative to the share in the US, normalized by the 2018 difference.

Second, we identify single cloud firms using Aberdeen again and estimate our empirical specification using only these firms. In Appendix C.3.2, we assess the reliability of Aberdeen data to identify the cloud provider used by the firms and show that Aberdeen data provides a useful but imperfect signal. Table OA-2 and Figure OA-11 present our estimates using this sample, which are quite similar to our baseline estimates across all outcomes. As discussed in the paper's main body, it is unlikely that the declines we observe are simply driven by substitution in usage to other providers.

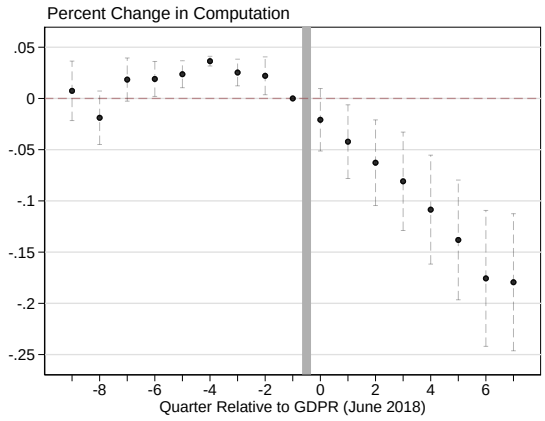
Finally, as discussed in Appendix B.1, the GDPR is likely to make multi-cloud usage more difficult. Thus, switching between cloud providers is more likely to occur on the *extensive* margin rather than the *intensive* margin. Thus, any cloud usage declines in a sample of firms that continuously use our provider are unlikely to be driven by switching between cloud providers. Table OA-3 presents estimates from a balanced panel of firms, where positive cloud computing usage is observed two years before and after the GDPR.

Figure OA-11: Event Study Estimates of the Effect of the GDPR on Cloud Inputs (Excluding Multi-Cloud Firms)

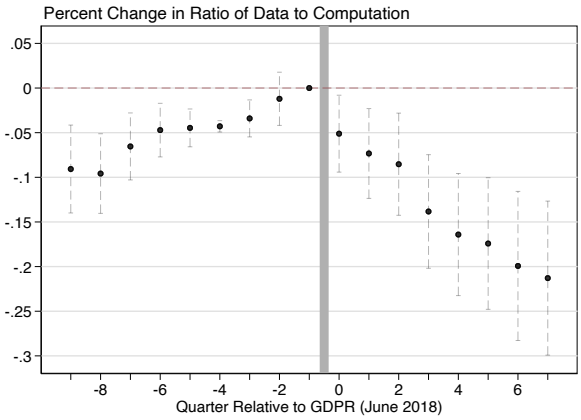
(a) Data



(b) Compute



(c) Data Intensity



Notes: Figure presents estimates of equation (1) of β_q, the coefficient on the quarter of the move interacted with our treatment indicator. The coefficient in the quarter before the GDPR's implementation is normalized to zero. The outcome in each subpanel is denoted by the subpanel title. Dashed bars represent the 95 percent confidence intervals, and standard errors are clustered at the firm level. Sample sizes are presented in Table OA-2. The sample is composed of firms that do not use multiple cloud computing providers.

Table OA-2: Short- and Long-Run Effects of the GDPR (Excluding Multi-Cloud Adopters)

	Data (1)	Compute (2)	Data Intensity (3)
Short-Run Effect	-0.128	-0.085	-0.061
	(0.020)	(0.019)	(0.023)
Long-Run Effect	-0.258	-0.170	-0.121
	(0.027)	(0.028)	(0.034)
Observations	944,982	530,123	328,973
US Firms	13,166	7,891	4,152
EU Firms	14,112	7,415	4,832

Notes: Table presents estimates of equation (2) of the short-run (δ_1) and long-run (δ_2) coefficients, which estimate the impact of the GDPR in the first and second year after the GDPR came into force. Column (1) estimates the effect on storage. Column (2) estimates the effect on computation. Column (3) presents estimates of the data intensity. The sample excludes multi-cloud firms as described in Appendix D. Industries are defined as the ten divisions classified by SIC codes, with the addition of a "software" division, which we carve out of the services division and define through SIC codes 7370 - 7377. Pre-GDPR size deciles are measured thirteen months before the GDPR. For data intensity, we define "size decile" as the interaction between storage and compute terciles when measured in the period. Standard errors are clustered at the firm level.

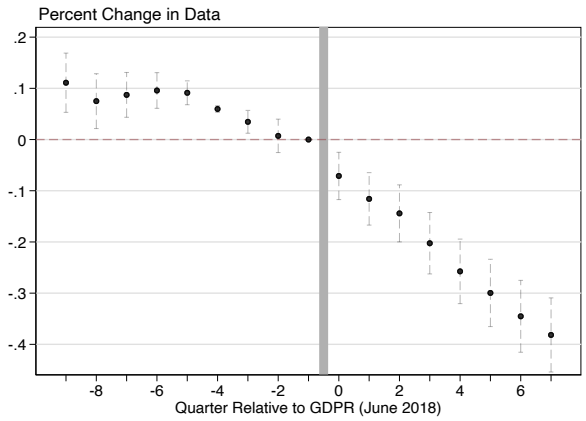
These estimated coefficients for the short-run and long-run effects of the GDPR are quite similar to our baseline estimates. In particular, they are consistent with our findings of a large decrease in both compute and storage alongside a decrease in data intensity. Thus, the results from our balanced panel in Table OA-3 and Figure OA-12 suggest that the declines in computation and storage we observe are not driven by switching between providers.

Substitution to On-Premises IT Next, we consider that firms might use both on-premises IT and cloud computing. To the extent that we cannot observe on-premises IT usage, declines in cloud computing may reflect re-allocations towards on-premises IT rather than true declines in computing. While increasing cloud computing adoption rates suggest that this margin may not play an important role, we consider the possibility that, after the GDPR was enacted, European firms might have changed allocation between cloud and on-premises IT differently from US firms.

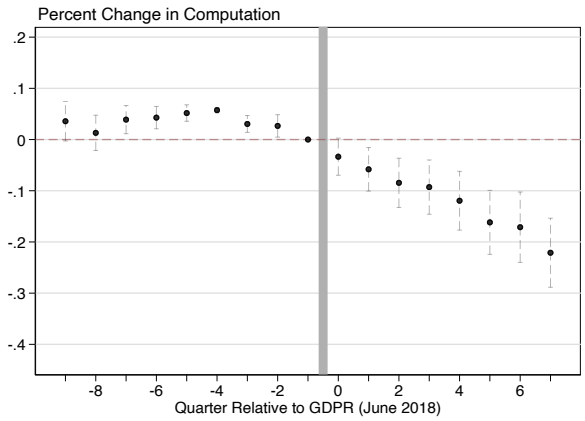
This would invalidate our identification arguments for the effects of compute and storage, although it would not necessarily affect the results on data intensity. To provide a robustness check for this, we focus on start-ups, which are unlikely to be using on-premises IT. These are young software firms that are less likely to switch to on-premise IT than more established firms due to the sizable upfront costs. In Table OA-4 and Figure OA-13, we

Figure OA-12: Event Study Estimates of the Effects of the GDPR on Cloud Inputs (Balanced Panel Estimates)

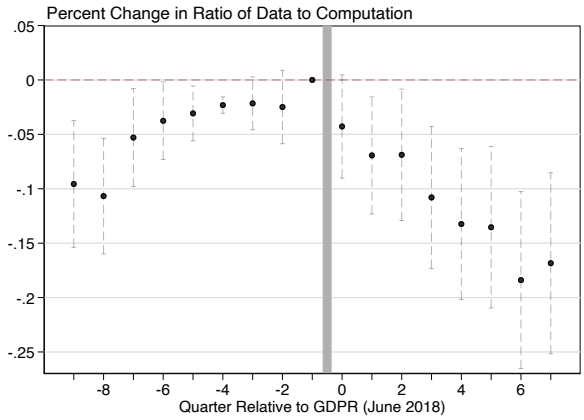
(a) Data



(b) Compute



(c) Data Intensity



Notes: Figure presents estimates of equation (1) of β_q, the coefficient on the quarter of the move interacted with our treatment indicator. The coefficient in the quarter before the GDPR's implementation is normalized to zero. The outcome in each subpanel is denoted by the subpanel title. Dashed bars represent the 95 percent confidence intervals, and standard errors are clustered at the firm level. Sample sizes are presented in Table OA-3. The sample is a balanced panel, and details can be found in Appendix Section D.

Table OA-3: Short- and Long-Run Effects of the GDPR (Balanced Panel)

	Data (1)	Compute (2)	Data Intensity (3)
Short-Run Effect	-0.221	-0.115	-0.046
	(0.024)	(0.020)	(0.027)
Long-Run Effect	-0.373	-0.205	-0.104
	(0.030)	(0.029)	(0.037)
Observations	608,562	363,793	227,022
US Firms	7,588	5,126	2,872
EU Firms	7,953	4,112	2,849

Notes: Table presents estimates of equation (2) of the short-run (δ_1) and long-run (δ_2) coefficients, which estimate the impact of the GDPR in the first and second year after the GDPR came into force. Column (1) estimates the effect on storage. Column (2) estimates the effect on computation. Column (3) presents estimates of the data intensity. The sample is a balanced panel, which is constructed as described in Appendix D. Industries are defined as the ten divisions classified by SIC codes, with the addition of a "software" division, which we carve out of the services division and define through SIC codes 7370 - 7377. Pre-GDPR size deciles are measured thirteen months before the GDPR. For data intensity, we define "size decile" as the interaction between storage and compute terciles when measured in the period. Standard errors are clustered at the firm level.

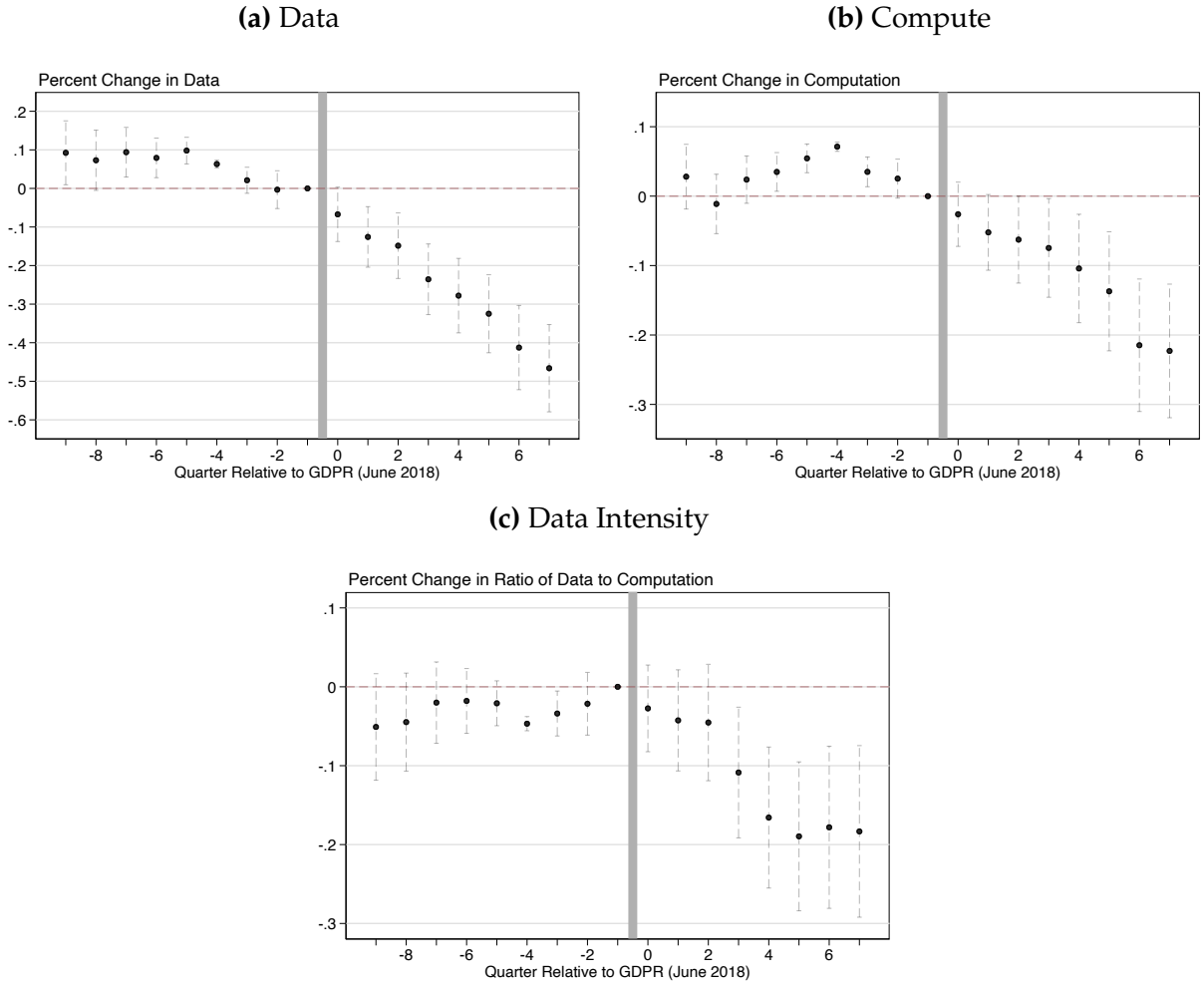
actually find larger effects for these firms rather than smaller effects. This suggests that the observed declines in computing and storage are unlikely to be driven by substitution to on-premises IT.

Table OA-4: Short- and Long-Run Effects of the GDPR (Start-Up Firms)

	Data (1)	Compute (2)	Data Intensity (3)
Short-Run Effect	-0.241	-0.100	-0.069
	(0.036)	(0.027)	(0.034)
Long-Run Effect	-0.424	-0.202	-0.165
	(0.047)	(0.040)	(0.049)
Observations	311,128	267,066	157,616
US Firms	4,550	4,101	2,190
EU Firms	3,819	3,179	1,974

Notes: Table presents estimates of equation (2) of the short-run (δ_1) and long-run (δ_2) coefficients, which estimate the impact of the GDPR in the first and second year after the GDPR came into force. Column (1) estimates the effect on storage. Column (2) estimates the effect on computation. Column (3) presents estimates of the data intensity. The sample is composed of start-up firms, classified according to a definition internal to the cloud provider. Industries are defined as the ten divisions classified by SIC codes, with the addition of a "software" division, which we carve out of the services division and define through SIC codes 7370 - 7377. Pre-GDPR size deciles are measured thirteen months before the GDPR. For data intensity, we define "size decile" as the interaction between storage and compute terciles when measured in the period. Standard errors are clustered at the firm level.

Figure OA-13: Event Study Estimates of the Effects of the GDPR on Cloud Inputs (Start-Up Firms)



Notes: Figure presents estimates of equation (1) of β_q, the coefficient on the quarter of the move interacted with our treatment indicator. The coefficient in the quarter before the GDPR's implementation is normalized to zero. The outcome in each subpanel is denoted by the subpanel title. Dashed bars represent the 95 percent confidence intervals, and standard errors are clustered at the firm level. Sample sizes are presented in Table OA-4. The sample is composed of start-up firms, where start-ups are labeled according to a definition internal to the cloud provider.

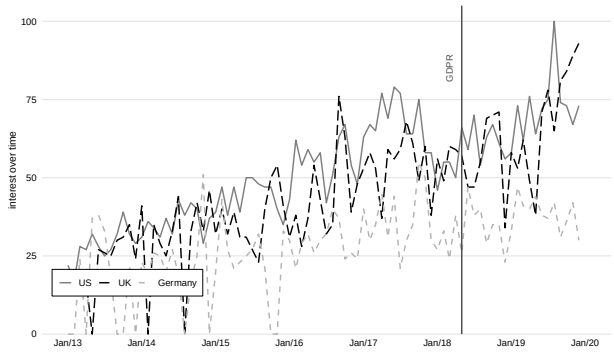
Hybrid Cloud To further consider whether differential hybrid cloud usage after GDPR could explain our results, we explore its importance across regions and compare it with the importance of cloud computing using Google Trends data. Google Trends compares the volume of search topics for a given term (e.g., "hybrid cloud") after anonymizing and standardizing data. We downloaded data for "hybrid cloud" and "cloud computing" in the United States, the United Kingdom, and Germany. Results are in Figure OA-14.

First, we compare the relative importance of hybrid cloud in Europe and in the US in

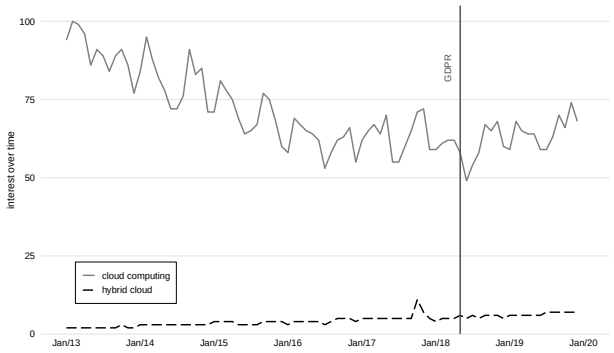
Figure OA-14(a). If differential take-up of hybrid cloud in the EU were to explain our results, then one would expect hybrid cloud searches to increase post-GDPR. We do not find evidence of this. Rather, relative interest in hybrid cloud computing in the EU, if anything, declines after the GDPR. Furthermore, although we focus on the United Kingdom and Germany in the EU due to language differences, the results are similar when we include searches from Italy, Spain, or France (both in English and in their respective languages). Second, Figure OA-14(b) compares interest in hybrid cloud and cloud computing worldwide from 2013 to 2021. Note that cloud computing is about 12 - 15 times more important as a term than hybrid cloud both before (March 2018) and after (December 2020) the GDPR.

Figure OA-14: Google Trends Data on Cloud Computing and Hybrid Cloud

(a) Hybrid Cloud in the US vs. in Europe



(b) Cloud Computing vs. Hybrid Cloud



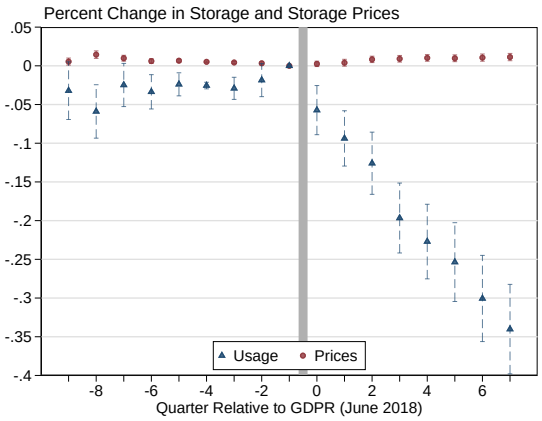
Notes: This figure compares Google Trends data for cloud computing and the hybrid cloud. Google Trends normalizes to 100 the topic-month with the most amount of searches. For example, a value of 50 on a given topic means that the topic is half as popular. Panel (a) plots the relative importance of the term "hybrid cloud" across the United States, the United Kingdom, and Germany. Panel (b) plots the relative importance of the terms “cloud computing” and “hybrid cloud” worldwide.

D.2 Price Changes

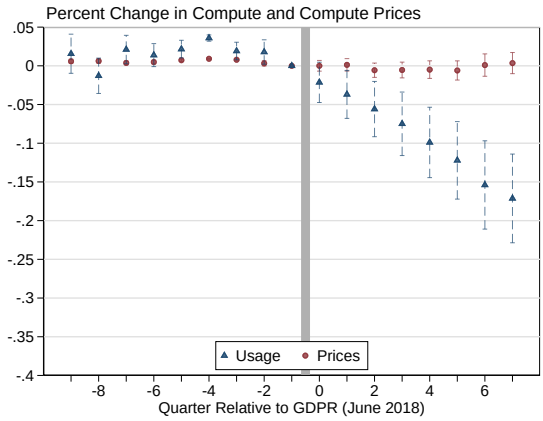
One natural channel through which the GDPR may have affected firms is through price changes in cloud computing. This would suggest our results might capture pricing responses by cloud providers rather than the GDPR’s direct impact on firms. For example, if cloud computing providers increase their prices in the European Union relative to the United States, this could confound our estimates. While conversations with internal employees suggest that there were no explicit pricing responses to the passage of the GDPR, we also examine the data for evidence of any differential pricing trends between the EU and the US, either in listed or paid prices. Figure OA-15 presents our results when we estimate our event study specification using paid prices as the outcome. We find no evidence of significant differential price changes.

Figure OA-15: Event Study Estimates of the Effect of the GDPR on Cloud Inputs (Effects on Paid Prices)

(a) Storage Prices



(b) Compute Prices



Notes: Figure presents estimates of equation (1) of β_q, the coefficient on the quarter of the move interacted with our treatment indicator. The coefficient in the quarter before the GDPR's implementation is normalized to zero. The outcome in each subpanel is denoted by the subpanel title. Dashed bars represent the 95 percent confidence intervals, and standard errors are clustered at the firm level. The dependent variables shown in blue are our baseline estimates. The dependent variable shown in red is the paid price for each product.

D.3 Websites and Cookie Collection

One of the most salient aspects of the GDPR is the requirement that firms receive consent for the collection of data. This is particularly important in the case of websites and cookies: post-GDPR, websites that need to collect personal information must get explicit consent. As studied by Aridor et al. (2023), there may also be selection in terms of which consumers choose to opt out of data collection and how valuable the remaining data is.

We aim to study whether our main effects are driven by the GDPR's effect on websites and how important the selection channel might be for our sample. To examine whether or not web usage is driving our effects, we turn towards Table OA-5, where we proxy for active website use through the usage of cloud-based web services. These are services provided by our cloud provider that firms use to host their websites.

Re-estimating our empirical specification using firms with and without websites, we indeed find that firms using web services seem to have been more affected by the GDPR regulations: the effects on storage and computing are roughly three times as large as those for non-active website users. However, the results remain statistically significant for non-active website users, and we additionally find that the adjustments in data intensity are similar. These results suggest that our effects are not solely driven by exposure to

Table OA-5: Short- and Long-Run Effects of the GDPR (Heterogeneous Effects by Cloud Adoption)

	Baseline	Web Users	Non-Web Users
	(1)	(2)	(3)
Panel A. Dependent variable: Log of Data			
Short-Run Effect	-0.129	-0.242	-0.080
	(0.018)	(0.020)	(0.010)
Long-Run Effect	-0.257	-0.421	-0.174
	(0.024)	(0.024)	(0.015)
Observations	1,143,149	255,057	888,092
US Firms	16,409	3,632	12,777
EU Firms	16,281	3,166	13,115
Panel B. Dependent variable: Log of Compute			
Short-Run Effect	-0.078	-0.124	-0.026
	(0.016)	(0.011)	(0.010)
Long-Run Effect	-0.154	-0.241	-0.060
	(0.024)	(0.018)	(0.019)
Observations	672,942	343,286	329,656
US Firms	10,294	5,243	5,051
EU Firms	8,927	4,297	4,630
Panel C. Dependent variable: Log of Data Intensity			
Short-Run Effect	-0.072	-0.066	-0.084
	(0.020)	(0.013)	(0.013)
Long-Run Effect	-0.131	-0.118	-0.112
	(0.029)	(0.023)	(0.024)
Observations	418,804	198,352	220,452
US Firms	5,487	2,714	2,773
EU Firms	5,872	2,608	3,264

Notes: Table presents estimates of equation (2) of δ_1 and δ_2, splitting our sample separately into firms that were observed using cloud-based web services with our provider between 24 and 13 months before the GDPR and those which were not. For comparison, Column (1) presents our baseline estimates across the full sample. Standard errors are clustered at the firm level.

the GDPR's web-based cookie consent requirements. Similarly, restricting our sample to firms with no listed websites (regardless of whether those websites are hosted by our cloud provider) yields qualitatively similar results. Results for the latter are available upon request.

D.4 Additional Robustness Exercises

Alternative Empirical Specifications The analyses in Section 4 are robust to several alternative specifications, including running our specification at the monthly level, the exclusion of various fixed effects, and alternative log-like transformation specification choices. Table OA-6 presents our event study results when the time periods are defined at the monthly level rather than at the quarterly level. In our main specification, we estimate coefficients and fixed effects at the quarterly level to preserve data confidentiality and improve precision. We find that our estimated coefficients are stable when we allow time trends to vary flexibly at the monthly level. The magnitudes of the estimated declines in storage, computation, and data intensity are comparable to our baseline results.

Table OA-6: Short- and Long-Run Effects of the GDPR (Monthly Specification)

	Data	Compute	Data Intensity
	(1)	(2)	(3)
Short-Run Effect	-0.141	-0.085	-0.079
	(0.018)	(0.017)	(0.021)
Long-Run Effect	-0.291	-0.174	-0.136
	(0.026)	(0.027)	(0.033)
Observations	1,143,149	672942	418,803
US Firms	16,409	10,294	5,487
EU Firms	16,281	8,927	5,872

Notes: Table presents estimates of equation (2) of δ_1 and δ_2, but where we allow our time trends to vary at the monthly level rather than the quarterly-level. Industries are defined as the ten divisions classified by SIC codes, with the addition of a "software" division, which we carve out of the services division and define through SIC codes 7370 - 7377. Pre-GDPR size deciles are measured thirteen months before the GDPR. For data intensity, we define "size decile" as the interaction between storage and compute terciles when measured in the period. Standard errors are clustered at the firm level.

We also consider the robustness of our analysis to the exclusion of our fixed effects. Our baseline specification allows for time trends to vary flexibly by industry and pre-GDPR size deciles. In the paper's Table 3, we consider alternative fixed effect specifications, including allowing time trends to vary only by industry and pre-GDPR size deciles and not allowing them to vary at all. We continue to observe the same features of our baseline

results, including large long-run declines in storage and compute, and moderate decreases in data intensity.

Finally, we consider alternative log-like transformations. Our baseline specification uses $\log(x)$. In Table OA-7 below, we consider using *asinh* and $\log(x + 1)$. We find essentially no difference between these transformations, suggesting that our results are not sensitive to the behavior of our outcome transformations around zero.

Table OA-7: Short- and Long-Run Effects of the GDPR (Alternative Transformations)

	Baseline (1)	*Asinh* (2)	*Log(x + 1)* (3)
Storage:			
Short-Run Effect	-0.129	-0.129	-0.126
	(0.018)	(0.018)	(0.019)
Long-Run Effect	-0.257	-0.257	-0.253
	(0.024)	(0.025)	(0.026)
Compute:			
Short-Run Effect	-0.078	-0.077	-0.076
	(0.016)	(0.016)	(0.016)
Long-Run Effect	-0.154	-0.153	-0.153
	(0.024)	(0.024)	(0.025)

Notes: Table presents estimates of equation (2) of the short-run (δ_1) and long-run (δ_2) coefficients, which estimate the impact of the GDPR in the first and second year after the GDPR came into force. Columns (1) - (3) compare our baseline log transformation with asinh and log(x+1) transformations, respectively. Industries are defined as the ten divisions classified by SIC codes, with the addition of a "software" division, which we carve out of the services division and define through SIC codes 7370 - 7377. Pre-GDPR size deciles are measured thirteen months before the GDPR. Standard errors are clustered at the firm level.

Alternative Sample Definitions We also discuss the robustness of our analyses in Section 4 to alternative sample definitions. In particular, we show that our estimated coefficients are relatively stable when conditioning on a different window of pre-GDPR usage, and when using a larger and more inclusive definition of "firms" where we don't require any internal or external industry or operating information.

First, we consider alternative windows of pre-GDPR usage. In our baseline sample, we use firms for whom we observe cloud usage continuously for a whole year exactly two years before the GDPR. Table OA-8 presents estimates from the samples constructed by instead conditioning on continuous observation one year before the GDPR (column 2) and both years before the GDPR (column 3).

Finally, we consider using a larger and more inclusive definition of "firms". Per Appendix C, we define firms in our baseline sample by requiring that there be either internal

Table OA-8: Short- and Long-Run Effects of the GDPR (Alternative Time Windows)

	(1)	(2)	(3)
Data:			
Short-Run Effect	-0.129	-0.101	-0.144
	(0.018)	(0.029)	(0.024)
Long-Run Effect	-0.257	-0.283	-0.299
	(0.024)	(0.039)	(0.034)
Compute:			
Short-Run Effect	-0.078	-0.078	-0.083
	(0.016)	(0.021)	(0.021)
Long-Run Effect	-0.154	-0.178	-0.178
	(0.024)	(0.033)	(0.033)
Data Intensity:			
Short-Run Effect	-0.072	-0.066	-0.063
	(0.020)	(0.023)	(0.023)
Long-Run Effect	-0.131	-0.128	-0.121
	(0.029)	(0.035)	(0.035)
Usage Observed During Year:			
Two Years Before GDPR	✓		✓
One Year Before GDPR		✓	✓

Notes: Table presents estimates of equation (2) of the short-run (δ_1) and long-run (δ_2) coefficients, which estimate the impact of the GDPR in the first and second year after the GDPR came into force. Column (1) shows our baseline specification. Column (2) conditions on observing firms for the year before GDPR (instead of two years before). Column (3) restricts the sample to firms continuously observed for the full two years before the GDPR. Industries are defined as the ten divisions classified by SIC codes, with the addition of a "software" division, which we carve out of the services division and define through SIC codes 7370 - 7377. Pre-GDPR size deciles are measured thirteen months before the GDPR. For data intensity, we define "size decile" as the interaction between storage and compute terciles when measured in the period. Standard errors are clustered at the firm level.

or external information on the firm's industry and country. In this larger sample, we drop the restriction that we must observe the firm's industry. Because there is no industry information, we amend the specification in Equation (2) so that fixed effects do not vary by industry. Table OA-9 below presents our estimates using this alternative sample.

Table OA-9: Short- and Long-Run Effects of the GDPR (More Inclusive Sample)

	Data (1)	Compute (2)	Data Intensity (3)
Short-Run Effect	-0.073	-0.059	-0.063
	(0.013)	(0.013)	(0.015)
Long-Run Effect	-0.151	-0.113	-0.117
	(0.018)	(0.020)	(0.022)
Observations	2,224,810	1,097,922	756,996
US Firms	34,876	18,037	10,807
EU Firms	31,622	15,004	10,299

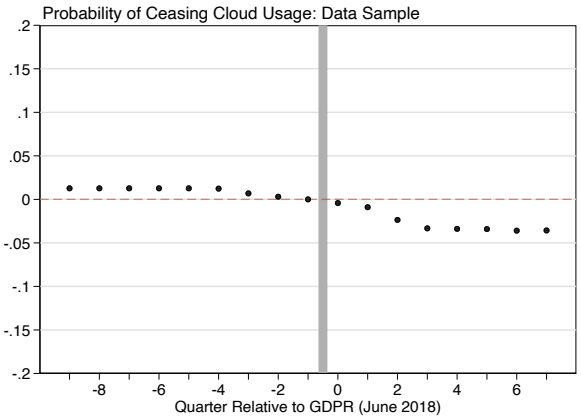
Notes: Table presents estimates of equation (2) of the short-run (δ_1) and long-run (δ_2) coefficients, which estimate the impact of the GDPR in the first and second year after the GDPR came into force. However, we do not allow the fixed effects to vary across industries (not all firms have industry information). Column (1) estimates the effect on storage. Column (2) estimates the effect on computation. Column (3) presents estimates of the data intensity. The sample incorporates firms for which we do not observe industry information, as described in Appendix D. Pre-GDPR size deciles are measured thirteen months before the GDPR. For data intensity, we define "size decile" as the interaction between storage and compute terciles when measured in the period. Standard errors are clustered at the firm level.

Extensive Margin Although Table OA-3 suggests that our baseline estimates are similar when we use a balanced panel of firms, we also directly examine whether the GDPR caused differential attrition between firms in the European Union and the United States. We study this using the same specification but replacing the outcome variable with an indicator for whether the firm has exited our sample. We present these results in Figure OA-16.

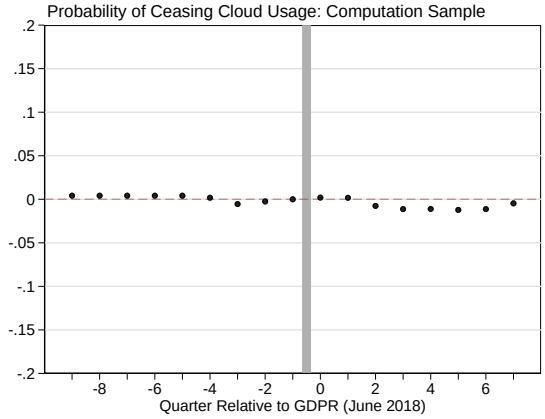
Matching Specification As an alternative to our baseline event-study specification, we implement a matching strategy. Specifically, we match each EU firm to US firms within the same industry and pre-GDPR cloud-usage decile, and then calculate the average firm-specific effects across firms. Figure OA-17 presents the results from this specification and shows that the estimates are extremely similar to those from our baseline event study.

Figure OA-16: Event Study Estimates of the Effects of the GDPR on Cloud Inputs (Differential Attrition)

(a) Data Sample

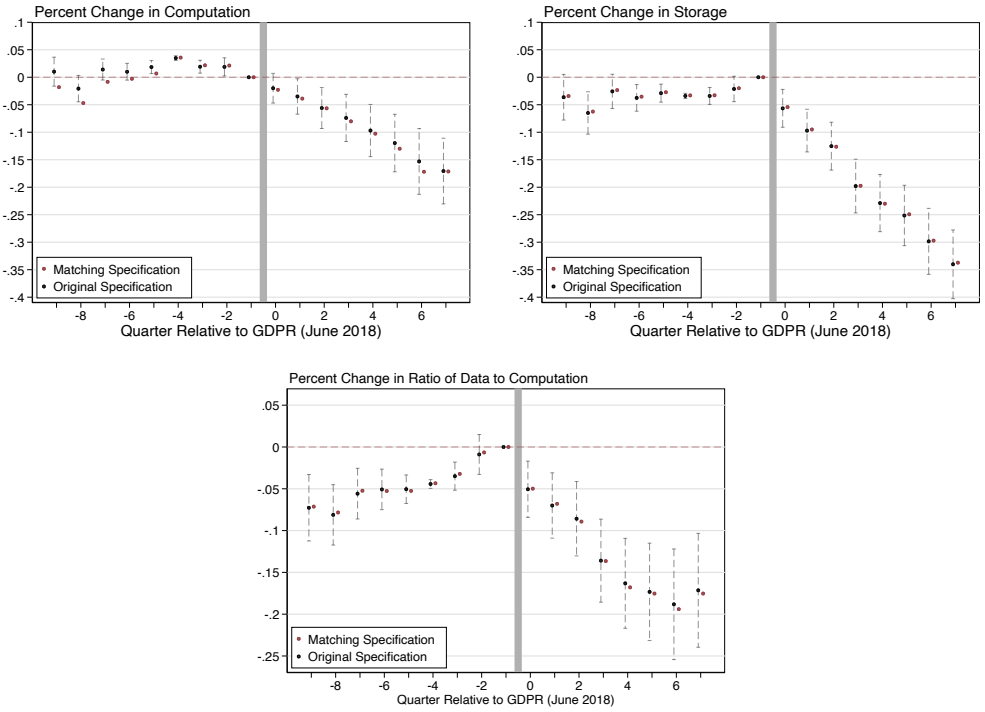


(b) Compute Sample



Notes: Figure presents estimates of equation (1) of β_q, the coefficient on the quarter of the move interacted with our treatment indicator. The coefficient in the quarter before the GDPR's implementation is normalized to zero. The outcome in each subpanel is denoted by the subpanel title. Dashed bars represent the 95 percent confidence intervals, and standard errors are clustered at the firm level. In contrast to the main figures, the dependent variable is an indicator of whether the firm has exited our sample.

Figure OA-17: Event Study Results Using Matching Specification



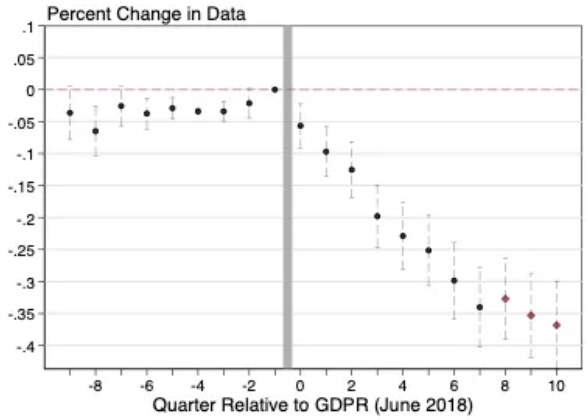
Notes: This figure shows event study results using a matching specification to compare treatment and control firms. Each EU firm is matched to US firms within the same industry and pre-GDPR cloud-usage decile.

Long-Run Effects To assess whether our estimates capture long-run effects or transitional dynamics, we extend the sample by three additional quarters. These quarters were previously omitted from our main specification to prevent overlap with COVID-19 and the implementation of the California Consumer Privacy Act. Figure OA-18 and Table OA-10 present these results.

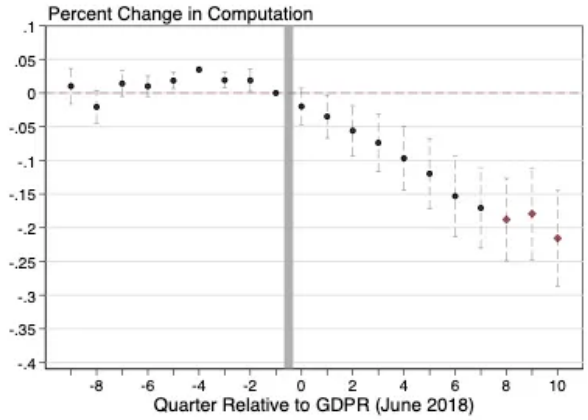
The extended results suggest that the effects begin to stabilize in 2021. For data intensity, the effect levels off and is essentially flat in the last year and a half of the sample. For data and computation, the gradual declines continue, but the trajectories flatten in the last four quarters. In particular, the estimated effect on data usage is 34% at seven quarters after the GDPR and 37% at ten quarters after the GDPR, suggesting a long-run effect of roughly 35–40%. We see a similar slowdown for the change in computation: the estimated effect is 19% at seven quarters and 22% at ten quarters after the GDPR. While these results should be interpreted with caution, given potential confounding effects from COVID-19 and the California Consumer Privacy Act, the additional quarters provide suggestive evidence that the long-run effects are close to those implied by our main specification.

Figure OA-18: Event Study Estimates of the Effects of the GDPR on Cloud Inputs (Extended Sample)

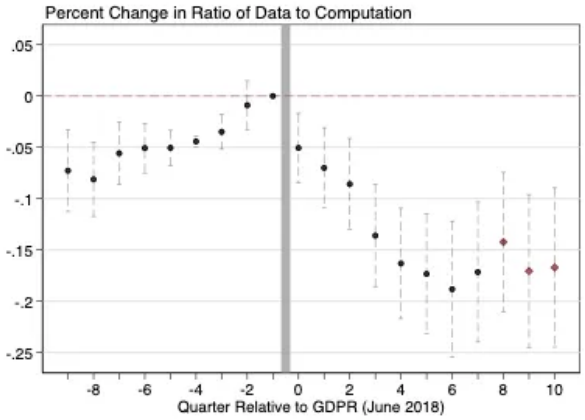
(a) Effect on Data



(b) Effect on Computation



(c) Effect on Data Intensity



Notes: This figure replicates Figure 3 using an extended sample that includes three additional quarters of data beyond the main analysis. These quarters were previously omitted to prevent overlap with COVID-19 and the implementation of the California Consumer Privacy Act.

Table OA-10: Short- and Long-Run Effects of the GDPR (Extended Sample)

	(1)	(2)	(3)	(4)
	Panel A. Dependent variable: Log of Data			
Short-Run Effect	-0.129	-0.132	-0.125	-0.134
	(0.018)	(0.017)	(0.017)	(0.017)
Long-Run Effect	-0.291	-0.298	-0.248	-0.269
	(0.028)	(0.028)	(0.028)	(0.028)
Observations	1,291,130	1,291,130	1,291,130	1,291,130
US Firms	16,409	16,409	16,409	16,409
EU Firms	16,281	16,281	16,281	16,281
	Panel B. Dependent variable: Log of Computation			
Short-Run Effect	-0.078	-0.082	-0.132	-0.148
	(0.016)	(0.016)	(0.016)	(0.016)
Long-Run Effect	-0.186	-0.203	-0.276	-0.317
	(0.027)	(0.027)	(0.027)	(0.027)
Observations	758,838	758,838	758,838	758,838
US Firms	10,294	10,294	10,294	10,294
EU Firms	8,927	8,927	8,927	8,927
	Panel C. Dependent variable: Log of Data Intensity			
Short-Run Effect	-0.072	-0.071	-0.025	-0.021
	(0.020)	(0.020)	(0.020)	(0.019)
Long-Run Effect	-0.123	-0.118	-0.034	-0.020
	(0.030)	(0.030)	(0.030)	(0.030)
Observations	535,496	535,496	535,496	535,496
US Firms	5,487	5,487	5,487	5,487
EU Firms	5,872	5,872	5,872	5,872
Time Trends Vary By:	Industry × Pre-GDPR Size Deciles	Pre-GDPR Size Deciles	Industry	-

Notes: This table replicates Table 3 using an extended sample that includes three additional quarters of data beyond the main analysis. These quarters were previously omitted to prevent overlap with COVID-19 and the implementation of the California Consumer Privacy Act. Standard errors are clustered at the firm level.

E Modeling Choices

This section explains our modeling choices, including our treatment of data as a variable input and our use of a CES production function.

E.1 Microfoundation for Data as a Variable Input

This section discusses alternative approaches to modeling data in production functions and provides a formal microfoundation for our choice to treat data as a variable input.

E.1.1 Modeling Data as an Input to Production

In our framework, we treat data as a variable input, motivated primarily by the cost structure of data storage and processing in the cloud. At the same time, data exhibits several features that make it resemble a dynamic input, such as capital. These include its accumulation over time, the presence of fixed costs associated with data extraction or acquisition, and the possibility that stored data affects future production and profits. In what follows, we first discuss how we conceptualize the role of data in firm production and then explain our modeling choice to treat data as a variable input.

There are two primary ways to conceptualize the role of data in firm production. The first one views data as an input that firms acquire in a market by incurring a per-unit cost. In this setting, data plays a role analogous to capital investment: firms hold a stock of data that may depreciate over time and periodically invest in additional data to augment this stock. The accumulated data stock is then used as an input in production.

A second perspective treats data as a byproduct of production. As firms serve customers, they generate data in the form of transaction records, consumer demographics, user behavior, and other information. Under this view, data differs from capital because firms do not incur a per-unit acquisition cost to expand their data stock. Instead, the relevant economic cost is a one-time fixed cost associated with building the infrastructure required to extract, process, and store data that is automatically generated as a consequence of production.

E.1.2 The Byproduct View of Data

In our view, the first channel, periodic data acquisition at a cost, closely resembles traditional capital dynamics, with the additional feature that firms incur per-unit storage costs for storing their data stock. The second channel, by contrast, is fundamentally different from capital accumulation and emphasizes the generation of data as a byproduct of firm

operations. While real firm behavior likely reflects a combination of these two mechanisms, both anecdotal evidence and the existing literature tend to emphasize the second channel. First, as emphasized in the literature (Goldfarb and Tucker, 2019; Bergemann and Bonatti, 2022), firms rarely pay customers directly for their data. While an industry of data brokers that sell data exists, anecdotal evidence suggests that the bulk of firms' datasets are generated through interactions with their own customers rather than purchased from these brokers.[62] Second, in the theoretical literature, many models treat data as a byproduct of economic activity generated through user behavior, sales records, and operational metrics (Jones and Tonetti, 2020; Farboodi and Veldkamp, 2026).

Under the byproduct view, data use can be viewed as a two-step process. First, firms invest in the capability to capture and store data as it is generated. These investments typically correspond to fixed infrastructure costs, such as building systems to record user clicks, monitor supply chains at a granular level, design interfaces to collect user information at sign-up, or establish internal reporting systems for employees. Once this fixed-infrastructure decision is made, the marginal cost of collecting byproduct data is minimal. After this investment, the firm, in each period, determines how much of this data flow to retain and how much to discard, given the data storage costs. This differs from the standard capital accumulation process because, under the byproduct view, there is no explicit and periodic costly data acquisition that adds to the firm's data stock; instead, data arise automatically from production, and the firm's decision problem centers on how much of this data to store.

In the context of cloud computing, this framework implies that data is best understood as a variable input. In each period, the firm chooses how much of the data it generates to retain and pays a variable cost proportional to its data stock every period. However, this view differs in important ways from the standard treatment of a variable input. In standard models, firms can purchase arbitrary quantities of a variable input on the spot market at a given price to maximize profit. By contrast, in our setting, the quantity of data a firm can use is limited by the flow of data generated as a byproduct of production. This requires additional conditions to consider data as a variable input.

E.1.3 Formal Model Sketch

To formalize these conditions, we consider a simple model of a firm's data accumulation. In this model, firms convert a share τ of their production into data. That is, after producing Y_t of output, the firm generates $\Delta \bar{D}_t = \tau Y_t$ units of new data, which becomes available for storage. For simplicity, we assume that τ is fixed (e.g., determined in the past by paying a

[62] See, for example, First-Party Data: Key Benefits and Challenges for Marketers.

fixed cost of building data collection infrastructure).

In our model, the firm decides how much of this byproduct data to store and how much to discard. Any stored data is added to the firm's data stock for use in production at time t and incurs storage costs of p_t^D every period. This makes the data storage decision dynamic: the amount of data retained today determines the data stock available in the future.

To formalize the timing, let D_{t-1} denote the firm's stock of data at the end of period $t-1$. At the beginning of period t, before production takes place, the firm chooses the amount of by-product data ΔD_{t-1} to add (or subtract) to its data stock, which gives the following data accumulation process

$$0 \leq D_t = D_{t-1} + \Delta D_{t-1}, \qquad \Delta D_{t-1} < \Delta \bar{D}_{t-1}$$

That is, the firm can add data to its data stock up to $\Delta \bar{D}_{t-1}$ and can freely discard existing data (so ΔD_{t-1} can be negative). Given the chosen data stock D_t, production in period t is given by

$$Y_t = F(X_t, D_t),$$

where X_t denotes other inputs (e.g., capital and labor), which we treat as static. The firm's recursive maximization problem then is (with a single state variable, the inherited data stock D_{t-1} for simplicity):

$$\begin{aligned} V(D_{t-1}) = \max_{D_t} &\left\{ \pi(X_t, D_t) - p_t^D D_t + \beta V(D_t) \right\} \\ \text{s.t.} \quad & 0 \leq D_t = D_{t-1} + \Delta D_{t-1}, \qquad \Delta D_{t-1} < \Delta \bar{D}_{t-1} \end{aligned}$$

where $V(D_t)$ denotes the value function, β is the discount factor, and the per-period cost of storing data, p_t^D, is included separately from the profit function for notational convenience. We next describe some high-level conditions under which this problem turns into a static problem.

Non-binding constraint and data as a variable input. Suppose the per-period availability constraint on data storage, $\Delta D_{t-1} < \Delta \bar{D}_{t-1}$, is never binding, that is, the firm's unconstrained optimal data decision for period t, D_t^*, always satisfies $D_t^* < D_{t-1}^* + \Delta \bar{D}_{t-1}$ for all t and the firm's beliefs about future are consistent with this assumption. Then the firm can freely choose the profit-maximizing quantity of data input each period without

worrying about future implications. This reduces the dynamic problem to a static problem:

$$\max_{\Delta D_t} \ \pi(X_t, D_t) - p_t^D D_t \tag{16}$$

Equivalently, under these assumptions, the optimal D_t satisfies the static FOC given the per-period storage prices. Because the firm can re-optimize how much data to store freely in the future, today's choice of D_t does not create a dynamic tradeoff.

For this derivation to be valid, we need the assumption that the data availability constraint must remain slack in every period. This requires the underlying conditions that shocks to productivity or demand are not too large from one period to the next, and the firm can generate enough by-product data every period. In particular, the marginal value of data must not increase so sharply that the firm would optimally be willing to store more than τY_{t-1} (if unconstrained), because that would induce firms to over-store data today in anticipation of insufficient byproduct data generation in the future, thereby making data a dynamic input that requires intertemporal optimization.

We acknowledge that these assumptions are strong and that, with ideal data availability, one should adopt a richer model of a firm's data use as an input in firm production. With such data, one could estimate a model of data accumulation that explicitly characterizes the technology of byproduct data generation and the role of data in the overall production function. However, the datasets required to implement such a model are not available in practice, and certainly not in our data. Consequently, we view our approach of modeling data as a variable input as a reasonable and tractable approximation to firms' data use in the cloud computing context.

E.2 Justification of CES Production Function

In our model described in Section 5.1, we assume a CES information production function that combines data and computation. This choice is motivated by the flexibility of the CES form in capturing different degrees of substitutability among inputs. Because there is no firm-level empirical evidence on the elasticity of substitution between data and computation, we avoid imposing a fixed elasticity of substitution, as in Cobb–Douglas or Leontief specifications. A key advantage of the CES production function is that it nests two polar cases: inputs may be perfect substitutes or perfect complements. The free elasticity-of-substitution parameter, therefore, allows us to capture a wide range of technologies within a single, parsimonious functional form.

However, the CES production function remains a parametric specification and therefore imposes important restrictions. Most notably, it assumes a constant elasticity of substitu-

tion that does not vary with input levels or across input pairs. While the latter limitation is not restrictive in our setting—since we focus on only two inputs—the former imposes a substantive constraint. In particular, it requires that data and computation have the same degree of substitutability across firms of different sizes, an assumption that may be unrealistic.

A more flexible alternative specification considered in the literature is

$$Y_{it} = F\big(X_{it},\, I_t(\omega_{it}^c C_{it}, D_{it})\big)\, \omega_{it},$$

where $F(\cdot)$ is a homothetic and separable production function (Demirer, 2025). Here, X_{it} denotes other inputs in the production function, while $I_t(\omega_{it}^c C_{it}, D_{it})$ represents the information production function that combines computation and data. The homothetic separability condition implies that C_{it} and D_{it} are separable from the other inputs X_{it} through a separate subproduction function $I_t(\cdot)$, and that $I_t(\cdot)$ itself is homothetic. This class of production functions is studied by Demirer (2025), who show that it implies the following first-order condition relating input ratios to price ratios:

$$\frac{C_{it}}{D_{it}} = h\left(\frac{p_{it}^d}{p_{it}^c},\, \omega_{it}^c\right), \tag{17}$$

where $h(\cdot)$ is a nonparametric function of the relative prices of data and computation and compute-augmenting productivity ω_{it}^c. The results in Demirer (2025) imply that $h(\cdot)$ is linearly separable (in logs) in ω_{it}^c if and only if $I_t(\cdot)$ takes a CES functional form. Consequently, relaxing the CES assumption requires estimating Equation (17) nonparametrically. For example, one could apply the approach of Imbens and Newey (2009) under appropriate support conditions and using an instrument that is independent of ω_{it}^c. While this is a promising direction for future research to deepen our understanding of the relationship between data and computation, it is infeasible in our setting due to the limited sample size.

However, we argue that the CES specification has the key flexibility, the free elasticity of substitution, which provides the crucial variation needed to estimate the cost of the GDPR from changes in the data-to-computation input ratio. To see this, consider the following intuition. We identify wedges from firms' adjustments of the data-to-compute ratio after the GDPR, while controlling for changes in relative prices. In this framework, the magnitude of the input-ratio response is governed by the elasticity of substitution, and different values of this elasticity can generate markedly different responses to the same cost shock.

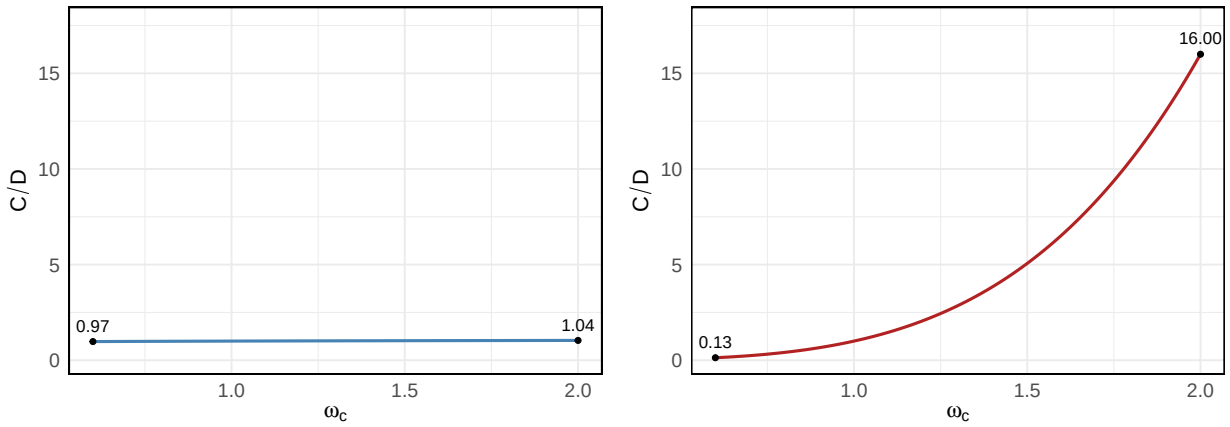
Consider the case in which data and computation are close to perfect substitutes in the production function. In this environment, the firm's input choice is driven almost entirely by relative prices. If data is cheap relative to computation, the firm will predominantly rely on data; conversely, if computation is cheaper, the firm will substitute toward computation. As a result, the ratio of data to computation inputs becomes large and highly sensitive to small changes in relative prices. Empirically, this implies that a large observed change in the input ratio may correspond to only a modest change in the underlying regulatory wedge. Put differently, when inputs are close substitutes, even small wedges can generate large swings in the observed data-to-computation ratio.

Now consider the opposite case, in which data and computation are close to perfect complements. In this setting, the inputs are used in nearly fixed proportions, so the data-to-computation ratio is largely unresponsive to changes in relative prices. Under this assumption, generating even small responses in the input ratio requires substantial changes in the underlying regulatory wedge. Put differently, when inputs are combined in near-fixed proportions, small deviations in the input ratio translate into extremely large implied changes in regulatory costs.

We illustrate this intuition in Figure OA-19, which plots the relationship between C/D and ω^c under two different values of the elasticity of substitution σ. When σ is small (Panel a), data and compute are close to complements, so changes in ω^c have little effect on the input ratio C/D. By contrast, when σ is large (Panel b), data and compute are close substitutes, and small changes in ω^c lead to large swings in C/D.

What does this imply? Imposing perfect substitutability would mechanically assume that the regulatory cost is small, whereas imposing perfect complementarity would, ex ante, assume that the regulatory cost is large. By leaving the elasticity of substitution as a free parameter and estimating it from the data, our framework avoids arbitrarily imposing either a high or a low regulatory cost. Instead, the magnitude of the implied cost is disciplined by data. As long as the elasticity of substitution is well identified—which in our setting relies only on price variation and yields precise estimates—the CES form does not impose *a priori* restrictions on whether the regulatory or information cost wedge is large or small.

Figure OA-19: Input Ratio Response to ω^c Under Different Elasticities



(a) $\sigma = 0.05$ (near-complements) **(b)** $\sigma = 4$ (near-substitutes)

Notes: Each panel plots C/D against ω^c for fixed $p_d/p_c = 1$ and $\gamma = 0$, with a common y-axis across panels. Values at the first and last C/D points are annotated on the curves. Panel (a) shows low sensitivity when σ is small; Panel (b) shows high sensitivity when σ is large.

F Technical Appendix

This section provides the derivation of the results in Section 5.

F.1 First-Order Conditions of Cost Minimization

Assume that firms produce according to the following production function:

$$F(X_{it}, I_{it}(C_{it}, D_{it}), \omega_{it}),$$

where I_{it} represents information, X_{it} is a vector of other observed inputs, and ω_{it} represents unobserved productivity. We assume that the information is produced according to the following technology:

$$I_{it} = \left(\omega_{it}^{c} C_{it}^{\rho} + \alpha D_{it}^{\rho}\right)^{1/\rho}.$$

We assume that firms choose variable inputs to minimize the cost of production by taking prices as given, which is a necessary condition for profit maximization. We also assume that firms take productivity ω_{it}^{c} as given in the static cost minimization problem. This cost minimization problem can be written as:

$$\min_{C_{it}, D_{it}, X_{it}^{v}} \quad p_{it}^{c} C_{it} + p_{it}^{d} D_{it} + p_{it}^{x} X_{it}^{v} \qquad \text{s.t.} \quad F(X_{it}, I_{it}, \omega_{it}) \geq \bar{Y}_{it},$$

where $\bar{Y}_{it}$ is the target level of production, X_{it}^{v} denotes variable inputs in X_{it}, and p_{it}^{x} denotes the input price vector of X_{it}^{v}. The FOCs with respect to C_{it} and D_{it} can be written as:

$$\begin{aligned}
\mu_{it} F_2(X_{it}, I_{it}, \omega_{it}) \left(\omega_{it}^{c} C_{it}^{\rho} + \alpha D_{it}^{\rho}\right)^{1/\rho - 1} C_{it}^{\rho - 1} \omega_{it}^{c} &= p_{it}^{c} \\
\mu_{it} F_2(X_{it}, I_{it}, \omega_{it}) \left(\omega_{it}^{c} C_{it}^{\rho} + \alpha D_{it}^{\rho}\right)^{1/\rho - 1} D_{it}^{\rho - 1} \alpha &= p_{it}^{d}
\end{aligned}$$

where μ_{it} is the Lagrange multiplier and F_2 denotes the derivative of F with respect to its second argument. Taking the ratio of the two FOCs, we obtain:

$$\frac{\alpha}{\omega_{it}^{c}} \left(\frac{C_{it}}{D_{it}}\right)^{1-\rho} = \frac{p_{it}^{d}}{p_{it}^{c}}$$

Taking the logarithm and rearranging the terms yields:

$$(1-\rho)\log\left(\frac{C_{it}}{D_{it}}\right) - \log(\omega_{it}^c) + \log(\alpha) = \log\left(\frac{p_{it}^d}{p_{it}^c}\right).$$

By using $\sigma = 1/(1-\rho)$ and defining $\gamma \equiv -\sigma\log(\alpha)$, we can obtain Equation (4) as presented in the main text:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma + \sigma\log\left(\frac{p_{it}^d}{p_{it}^c}\right) + \sigma\log(\omega_{it}^c).$$

F.2 Including Labor in Information Production Function

In this section, we demonstrate that the derivation of the FOCs remains valid even if the information production function includes labor input in the CES form. We consider labor in the information production function because firms might require software engineers to process data. To illustrate this scenario, we consider a nested CES form where data and computation are nested:

$$I_{it} = \left(\left(\omega_{it}^c C_{it}^\rho + \alpha_D D_{it}^\rho\right)^{v/\rho} + \alpha_L L_{it}^v\right)^{1/v}$$

where v is the substitution parameter between information and labor. Taking the FOCs with respect to C_{it} and D_{it}, we obtain:

$$\mu_{it}F_2(X_{it}, I_{it}, \omega_{it})\left(\left(\omega_{it}^c C_{it}^\rho + \alpha_D D_{it}^\rho\right)^{v/\rho} + \alpha_L L_{it}^v\right)^{1/v-1}\left(\omega_{it}^c C_{it}^\rho + \alpha_D D_{it}^\rho\right)^{v/\rho-1} C_{it}^{\rho-1}\omega_{it}^c = p_{it}^c$$

$$\mu_{it}F_2(X_{it}, I_{it}, \omega_{it})\left(\left(\omega_{it}^c C_{it}^\rho + \alpha_D D_{it}^\rho\right)^{v/\rho} + \alpha_L L_{it}^v\right)^{1/v-1}\left(\omega_{it}^c C_{it}^\rho + \alpha_D D_{it}^\rho\right)^{v/\rho-1} D_{it}^{\rho-1}\alpha_D = p_{it}^d$$

Taking the ratio of these FOCs yields the same equation as above:

$$\frac{\alpha_D}{\omega_{it}^c}\left(\frac{C_{it}}{D_{it}}\right)^{1-\rho} = \frac{p_{it}^d}{p_{it}^c}$$

Therefore, the information production function can accommodate labor. It is important to note that this result relies on the specific nested CES functional form used in this analysis. For instance, if data and labor were in the same nest with computation in a different one, the ratio of FOCs would involve labor, and our equivalence result would break down.

F.3 Extensions to the GDPR as a Cost Shock to Data

In this section, we show how our estimates of the wedge induced by the GDPR (λ) would change under alternative assumptions about how the GDPR impacts firms' information production functions. This section builds on details of our identification and estimation procedure described in Section 5.3.

F.3.1 Existing Pre-GDPR Wedges

First, we consider the case in which there are other unobserved variable costs to using data that generate wedges even before the GDPR. For example, these could be costs associated with collecting customer and employee data. In this case, our estimates capture the *additional* wedges driven by the GDPR between the marginal product of data and its price. In particular, consider the following model of data costs faced by each firm i:

$$\textbf{Pre-GDPR:} \quad \tilde{p}^d_{it} = (1 + \lambda^0_i) p^d_{it}, \qquad \textbf{Post-GDPR:} \quad \tilde{p}^d_{it} = (1 + \lambda^1_i) p^d_{it}.$$

Under this assumption, our pre-GDPR equation–from which we estimate the firm-specific compute augmenting productivity–becomes:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma + \sigma_1 \log\left(\frac{p^d_{it}}{p^c_{it}}\right) + \sigma_1\Big(\log(\omega^c_i) + \log(1 + \lambda^0_i)\Big) + \sigma_1 \log(\phi^c_t) + \sigma_1 \log(\eta_{it}),$$

so our first-step estimation cannot separately identify ω^c_i from λ^0_i (our estimating equation recovers $\log(\omega^c_i) + \log(1 + \lambda^0_i)$ instead of $\log(\omega^c_i)$ under the paper main assumptions).

In the post-GDPR period, the FOCs will be given by:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma_2 + \sigma_2\Big(\log\left(\frac{p^d_{it}}{p^c_{it}}\right) + \log(\phi^c_t)\Big) + \sigma_2\Big(\log(1 + \lambda^1_i) + \log(\omega^c_i)\Big) + \sigma_2 \log(\eta_{it}),$$

So in the second step, our estimation procedure recovers $\log(1 + \lambda^1_i) + \log(\omega^c_i)$ as the fixed effects. In order to identify the wedges, we subtracted the first-step firm-fixed effect estimates (which estimates $\log(\omega^c_i)$ under our assumptions) from the second-step fixed effects. However, in the model described in this section, the first step recovers an estimate of $\log(\omega^c_i) + \log(1 + \lambda^0_i)$ as firm fixed effects. Therefore, subtracting the first-step estimate $\log(\omega^c_i) + \log(1 + \lambda^0_i)$ from the second-step estimate $\log(1 + \lambda^1_i) + \log(\omega^c_i)$ will yield:

$$\log(1 + \lambda^1_i) - \log(1 + \lambda^0_i)$$

Therefore, our procedure recovers $(1 + \lambda^1_i)/(1 + \lambda^0_i) - 1$ as the wedge under the model

described in this section, which is the additional multiplicative wedge due to the GDPR.

F.3.2 Negative Productivity Shock to Data-Augmenting Productivity

Our main text assumes that the production function has compute-augmenting productivity. Here, we consider an alternative assumption that productivity is data-augmenting:

$$I_{it}(C_{it}, D_{it}) = \left(\alpha C_{it}^{\rho} + \tilde{\omega}_{it}^{d} D_{it}^{\rho}\right)^{1/\rho},$$

where $\tilde{\omega}_{it}^{d}$ denotes data-augmenting productivity, which can potentially be affected by the GDPR. In particular, we specify $\tilde{\omega}_{it}^{d}$ as:

$$\textbf{Pre-GDPR:} \quad \tilde{\omega}_{it}^{d} = \omega_{it}^{d}, \qquad\qquad \textbf{Post-GDPR:} \quad \tilde{\omega}_{it}^{d} = (1 + \lambda_{i}^{d})\omega_{it}^{d}.$$

where ω_{it}^{d} is the counterfactual data-augmenting productivity in the absence of the GDPR. Here, $\lambda^{d} \leq 0$ corresponds to a negative productivity shock to data-augmenting productivity. Under these assumptions, the FOC in the pre-GDPR period becomes:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma + \sigma \log\left(\frac{p_{it}^{d}}{p_{it}^{c}}\right) - \sigma \log(\omega_{it}^{d}).$$

Therefore, our first stage procedure recovers firm-specific data-augmenting productivity (formally $-\log \omega_{it}^{d}$) instead of compute-augmenting productivity ($\log \omega_{it}^{c}$). Under the assumption that the GDPR affects the productivity of data, the production function in the post-GDPR period becomes

$$I_{it}(C_{it}, D_{it}) = \left(\alpha C_{it}^{\rho} + \omega_{it}^{d}(1 + \lambda_{i}^{d}) D_{it}^{\rho}\right)^{1/\rho}, \tag{18}$$

Taking the FOCs after the GDPR, we obtain

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma + \sigma \log\left(\frac{p_{it}^{d}}{p_{it}^{c}}\right) - \sigma \log(\omega_{it}^{d}) - \sigma \log(1 + \lambda_{i}^{d}). \tag{19}$$

Compare Equation (19) with our post-GDPR FOC in the main text (Equation (9) reproduced below without the changes in the elasticity of substitution for simplicity):

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma + \sigma \log\left(\frac{p_{it}^{d}}{p_{it}^{c}}\right) + \sigma \log(1 + \lambda_{i}) + \sigma \log(\omega_{it}^{c}).$$

Since we recovered $-\sigma \log(\omega_{it}^{d})$ in the first step, our estimation procedure recovers

$\sigma \log(1+\lambda_i)$ as $-\sigma \log(1+\lambda_i^d)$ from Equation (19). Now we can solve for λ_i as a function of λ_i^d from the relationship $1+\lambda_i = 1/(1+\lambda_i^d)$ which yields:

$$\lambda_i = \frac{-\lambda_i^d}{1+\lambda_i^d},$$

and for small λ_i^d, we obtain $\lambda_i \approx -\lambda_i^d$ so our procedure recovers the magnitude of the shock to data productivity due to GDPR. For larger values of λ_i, we can use the exact formula to estimate changes. For example, in the paper, we estimate $\lambda_i \approx 1/5$ on average, which implies that $\lambda_i^d \approx -1/6$ under this alternative assumption.

F.3.3 Wedges in Both Data and Computation

In our main text, we assume that GDPR only affects data costs. Here, we consider the case in which the GDPR affects both computation and data so that:

$$\textbf{Pre-GDPR:} \quad \tilde{p}_{it}^d = p_{it}^d, \quad \tilde{p}_{it}^c = p_{it}^c, \quad \textbf{Post-GDPR:} \quad \tilde{p}_{it}^d = (1+\lambda_i^d)p_{it}^d, \quad \tilde{p}_{it}^c = (1+\lambda_i^c)p_{it}^c.$$

Taking first-order conditions post-GDPR under this assumption, we obtain:

$$\log\left(\frac{C_{it}}{D_{it}}\right) = \gamma + \sigma_2 \log\left(\frac{p_{it}^d}{p_{it}^c}\right) + \sigma_2 \log\left(\frac{1+\lambda_i^d}{1+\lambda_i^c}\right) + \sigma_2 \log(\omega_i^c) + \sigma_2 \log(\phi_t^c) + \sigma_2 \log(\eta_{it}),$$

which differs from the main text (Equation 9) only through having the ratio of wedges instead of data wedge. Therefore, in this case, our estimation procedure identifies $(1+\lambda_i^d)/(1+\lambda_i^c)$ instead of only $(1+\lambda_i^d)$, which introduces downward bias for λ_i^d if $\lambda_i^c > 0$. Since λ_i^d would be underestimated while we assume $\lambda_i^c = 0$, we would underestimate the total cost of GDPR.

F.4 Derivation for Cost of Information

In this subsection, we derive the formula for the cost of information given by Equation (11) in the paper. Next, we generalize the cost of information for any monotonic transformation of the information production function (e.g., assuming increasing/decreasing returns to scale in the information production function). We then conclude by showing how the percentage changes in the cost of information, as computed in the paper, are invariant to monotonic transformations. To ease notation, we drop the subscripts and use p_c, p_d and ω in the place of p^c, p^d and ω^c.

Consider the optimal isocline as given by the FOC from data and computation:

$$\frac{\alpha}{\omega}\left(\frac{C}{D}\right)^{1-\rho} = \frac{p_d}{p_c} \quad \Longleftrightarrow \quad D = \left(\frac{\omega}{p_c}\frac{p_d}{\alpha}\right)^{\frac{1}{\rho-1}} C, \tag{20}$$

which relates the optimal data input usage D to the optimal computation usage C.

To obtain the information production as a function of parameters, we substitute Equation (20) into the information production function:

$$I = \left(\omega C^{\rho} + \alpha\left(\frac{\omega}{p_c}\frac{p_d}{\alpha}\right)^{\frac{\rho}{\rho-1}} C^{\rho}\right)^{1/\rho} = \left(\frac{\omega}{p_c}\right)^{\frac{1}{\rho-1}} \left(p_c\left(\frac{p_c}{\omega}\right)^{\frac{1}{\rho-1}} + p_d\left(\frac{p_d}{\alpha}\right)^{\frac{1}{\rho-1}}\right)^{1/\rho} C \tag{21}$$

and defining Φ as:

$$\Phi = \left(p_c\left(\frac{p_c}{\omega}\right)^{\frac{1}{\rho-1}} + p_d\left(\frac{p_d}{\alpha}\right)^{\frac{1}{\rho-1}}\right),$$

we can simplify Equation (21) as:

$$I = \Phi^{1/\rho}\left(\frac{\omega}{p_c}\right)^{\frac{1}{\rho-1}} C \implies C^*(I,p) = \frac{I}{\Phi^{1/\rho}}\left(\frac{p_c}{\omega}\right)^{\frac{1}{\rho-1}} \text{ and } D^*(I,p) = \frac{I}{\Phi^{1/\rho}}\left(\frac{p_d}{\alpha}\right)^{\frac{1}{\rho-1}}$$

so we obtain the optimal input demands as a function of prices and parameters. Now, substituting them into the cost of information:

$$CI^*(I,p) = p_c C^* + p_d D^* = \frac{I}{\Phi^{1/\rho}} \underbrace{\left(p_c\left(\frac{p_c}{\omega}\right)^{\frac{1}{\rho-1}} + p_d\left(\frac{p_d}{\alpha}\right)^{\frac{1}{\rho-1}}\right)}_{\phi} = I\Phi^{\frac{\rho-1}{\rho}}.$$

To get to the final result, note that $(\rho-1)/\rho = 1/(1-\sigma)$, and $1/(\rho-1) = -\sigma$. Therefore, we can express the cost of information as a function of I, prices, and parameters:

$$CI^*(I,p) = I\left(\omega^{\sigma} p_c^{1-\sigma} + \alpha^{\sigma} p_d^{1-\sigma}\right)^{1/(1-\sigma)},$$

which is the main equation in the paper.

Next, we derive the cost of information for any monotonic transformation of the production function of I. As we argued in Section 5.1, I does not have a natural scale and can be defined only up to a monotonic transformation. For any monotonic transformation of

I, $h(I)$, the cost function can be obtained as:

$$CI^*(I_{it}, p_{it}) = h^{-1}(I)\left(\omega^\sigma p_c^{1-\sigma} + \alpha^\sigma p_d^{1-\sigma}\right)^{1/(1-\sigma)}. \tag{22}$$

To see this, note that when substituting Equation (20) into the production function we get Equation (21)' as given by:

$$h^{-1}(I) = \left(\frac{\omega}{p_c}\right)^{\frac{1}{\rho-1}} \left(p_c \left(\frac{p_c}{\omega}\right)^{\frac{1}{\rho-1}} + p_d \left(\frac{p_d}{\alpha}\right)^{\frac{1}{\rho-1}}\right)^{1/\rho} C,$$

while the rest of the algebra stays the same, but replacing I with $h^{-1}(I)$.

Finally, to show that the *percentage* change in the cost of information is invariant to monotonic transformations, notice that at any information level I, we can take the ratio of Equation (22) with and without the GDPR wedge and subtract one to obtain the percentage change in the cost of information:

$$1 + \Delta CI^*(I_{it}, p_{it}) = \left[\frac{\omega^\sigma p_c^{1-\sigma} + \alpha^\sigma \left((1+\lambda_i)p_d\right)^{1-\sigma}}{\omega^\sigma p_c^{1-\sigma} + \alpha^\sigma p_d^{1-\sigma}}\right]^{1/(1-\sigma)}, \tag{23}$$

which is the main formula we use in the paper.

F.5 Cost of Information Decomposition

In this section, we derive the formula for the decomposition of the cost of information. We drop all subscripts to ease notation and start by substituting the values for the cost-minimizing information cost, CI^*, as:

$$CI^*(I, p, \lambda) = p_c C^*(I, p, \lambda) + p_d(1+\lambda)D^*(I, p, \lambda),$$

where $C^*(I, p, \lambda)$ and $D^*(I, p, \lambda)$ are the optimal compute and data choices as a function of information level, input prices, and wedges. We will remove the function arguments to ease the notation even more. The total derivative with respect to λ is obtaining by differentiating both sides with respect to λ:

$$\frac{\mathrm{d}CI^*}{\mathrm{d}\lambda} = p_c \frac{\mathrm{dC}^*}{\mathrm{d}\lambda} + p_d D^* + p_d(1+\lambda)\frac{\mathrm{dD}^*}{\mathrm{d}\lambda}.$$

Multiplying both sides by λ/CI^* we obtain:

$$\frac{\mathrm{d}CI^*}{\mathrm{d}\lambda}\frac{\lambda}{CI^*} = p_c\frac{\mathrm{dC}^*}{\mathrm{d}\lambda}\frac{\lambda}{CI^*} + \lambda\left(\frac{p_dD^*}{CI^*}\right) + p_d(1+\lambda)\frac{\mathrm{dD}^*}{\mathrm{d}\lambda}\frac{\lambda}{CI^*}.$$

Rearranging terms and multiplying the first term by C^*/C^*, and the third by D^*/D^* we get

$$\frac{\mathrm{d}CI^*}{\mathrm{d}\lambda}\frac{\lambda}{CI^*} = \lambda\left(\frac{p_dD^*}{CI^*}\right) + \left(\frac{p_cC^*}{CI^*}\right)\left[\frac{\mathrm{dC}^*}{\mathrm{d}\lambda}\frac{\lambda}{C^*}\right] + \left(\frac{p_d(1+\lambda)D^*}{CI^*}\right)\left[\frac{\mathrm{dD}^*}{\mathrm{d}\lambda}\frac{\lambda}{D^*}\right],$$

and finally, recognizing that the terms in parentheses are the expenditure shares s_d and s_c, and the terms in squared parentheses are the elasticities, we get to the following equation:

$$\varepsilon(CI^*_{it},\lambda_i) = s^d_{it}\cdot\lambda_i + \left[s^d_{it}\cdot\varepsilon(D^*_{it},\lambda_i) + s^c_{it}\cdot\varepsilon(C^*_{it},\lambda_i)\right].$$

G Production Function Model Estimation Details

This section provides details on cloud computing pricing, the instrumental variable strategy, our estimation procedure, and intuition for our identification.

G.1 Cloud Computing Pricing

Our estimation of the elasticity of substitution is identified by how firms adjust their input demand to price changes. To provide context for the main sources of price variation, this section presents an overview of cloud computing pricing.

Cloud computing providers typically consider various factors when selecting pricing across locations. These factors may include electricity costs, availability of skilled labor, real estate costs, tax incentives, regulatory requirements, and the availability and cost of network connectivity. Additionally, firms may consider the level of competition in each location and the pricing strategies of different cloud providers.

Pricing for cloud services over the last decade has been characterized by a steady decline across all providers. As cloud providers have achieved economies of scale and improved their technological infrastructure, they have been able to offer lower prices to customers. In addition, increased competition among cloud providers to attract customers has contributed to lower prices. Byrne et al. (2018) constructs a price index for AWS over the last decade and investigates how prices have evolved. They found that AWS compute prices fell at an average annual rate of about 7%, database prices at more than 11%, and storage disk prices at more than 17%. Part of this price decline is driven by competition. Byrne et al. (2018) finds that AWS prices dropped more significantly when Microsoft Azure entered the market, at 10.5%, 22%, and about 25% for computation, database, and storage, respectively, between 2014 and 2016.

Overall, the last decade has seen a notable decline in cloud prices despite rising demand. This suggests that factors such as competition and technological advances have been the major drivers of cloud pricing in the last decade.

G.2 Instrumental Variable Strategy

Our instrumental variable strategy relies on the assumption that firms' data center location choices are persistent. This assumption is based on the observation that moving large datasets between data centers is typically costly. The cost of moving data to another data center in cloud computing can depend on several factors, including the amount of data being transferred, the distance between the source and destination data centers, and the pricing policies of the cloud service provider (García-Dorado and Rao, 2015). Some cloud

service providers may charge a fee for data transfer, and there may be additional costs associated with data migration, such as network bandwidth charges, storage costs, and downtime or disruption to services during the migration process.[63] Even though the specific costs and risks of data migration will depend on the migration plan and the cloud service provider, it is typically considered too costly by industry experts.

We leverage persistence in data center location arising from switching costs to design a shift-share instrumental variable strategy. Formally, each firm has exposure to different locations and pays different prices in each location due to variations in list prices and firm-specific discounts. We denote firm-specific price indices by p_{it}^d and p_{it}^c for data and computation, respectively. This price may be endogenous because the firm may receive discounts due to long-term commitments or adjust its exposure across locations based on productivity. To instrument for these prices, we use the list prices of storage at location l, denoted p_{lt}. This price is plausibly exogenous to changes in firm productivity because, after controlling for industry-specific trends, no firm is likely to affect list prices in a specific location. Additionally, we further purge these shares of endogeneity by using lag shares, as contemporaneous shares may be susceptible to reverse causality.

To obtain firm-specific price indices, we simply calculate the unit price paid by the firm by dividing the monthly total spending on compute and storage by the total quantity of compute and storage, respectively. This yields firm-specific compute and storage price indices that may vary due to discounts from long-term commitments or location-specific price variations. We divide the price of storage by the price of computation to obtain a firm-specific storage-to-computation price ratio, which is used in estimating the production function. Since this ratio is sensitive to outliers arising from small denominators, we winsorize these variables at the top and bottom 2 percentiles. We also construct the compute-to-storage usage ratio for each firm and apply the same winsorization procedure.

To construct the instruments, we proceed in two steps. Let p_{klt} denote the list price of product k in data center location l at time t, and let q_{iklt} denote firm i's total usage of product k in location l at time t. We denote the sets of compute and storage products by $\mathcal{K}_c$ and $\mathcal{K}_d$, respectively. In the first step, for each firm i and data center location l, we construct a location-specific price index as a weighted average of the retail prices of products in that location. The lagged product share of product k within location l is:

$$w_{kl(t-10)}^c = \frac{\sum_i q_{ikl(t-10)}}{\sum_{i,k' \in \mathcal{K}_c} q_{ik'l(t-10)}}, \qquad w_{kl(t-10)}^d = \frac{\sum_i q_{ikl(t-10)}}{\sum_{i,k' \in \mathcal{K}_d} q_{ik'l(t-10)}}.$$

[63] See detailed information on data transfer costs for top cloud computing providers at AWS Data Transfer Costs, Azure Bandwidth Pricing, and Google Cloud Storage Transfer Pricing.

The location-specific price index in location l is then:

$$p^c_{lt} = \sum_{k \in \mathcal{K}_c} w^c_{kl(t-10)}\, p_{klt}, \qquad p^d_{lt} = \sum_{k \in \mathcal{K}_d} w^d_{kl(t-10)}\, p_{klt}.$$

In the second step, we construct an instrument as a weighted average of the location-specific price indices, using lagged location shares as weights. The lagged location share for firm i in location l is:

$$s^c_{il(t-10)} = \frac{\sum_{k \in \mathcal{K}_c} q_{ikl(t-10)}}{\sum_{k' \in \mathcal{K}_c, l'} q_{ik'l'(t-10)}}, \qquad s^d_{il(t-10)} = \frac{\sum_{k \in \mathcal{K}_d} q_{ikl(t-10)}}{\sum_{k' \in \mathcal{K}_d, l'} q_{ik'l'(t-10)}}.$$

The instrument is then given by:

$$z^c_{it} = \sum_{l \in \mathcal{L}} s^c_{il(t-10)}\, p^c_{lt}, \qquad z^d_{it} = \sum_{l \in \mathcal{L}} s^d_{il(t-10)}\, p^d_{lt}.$$

If firm i had no usage of a product at a given location in the lagged period, we set its usage to zero. Since we use 10 months of lagged usage to construct exposure shares, we drop the first 10 months of observations for each firm when implementing this instrumental variable strategy. Finally, we use z^c_{it}/z^d_{it} to instrument for p^c_{it}/p^d_{it} in the production function estimation.

G.3 Estimation Details

Our identification strategy relies on the assumption that, in the absence of the GDPR, the industry-specific trend in compute productivity in the EU would have followed that of US firms, and that firm-specific compute technology would not have changed post-GDPR. To operationalize these assumptions, we follow a two-step estimation strategy.

In the first step, we estimate the following equation for US firms using the entire sample period with our IV strategy:

$$\log\left(\frac{C_{ikt}}{D_{ikt}}\right) = \gamma + \sigma^{US} \log\left(\frac{p^d_{ikt}}{p^c_{ikt}}\right) + \sigma^{US} \log(\omega^c_{ik}) + \sigma^{US} \log(\phi^c_{kt}) + \sigma^{US} \log(\eta_{ikt}), \tag{24}$$

where k denotes the 2-digit SIC industry to which firm i belongs.[64] This means that, although we estimate this equation for three broad industry categories (software, services, and manufacturing), we allow industry-specific trends to differ at the 2-digit level. When

[64] To maintain sufficient sample size and estimation precision, we combine industries with fewer than 50 firms into a single category.

estimating this equation, we normalize γ to zero because it is not separately identified from the levels of industry-specific trend and firm-specific compute productivity. We also normalize $\log(\phi^c_{k1})$ to 1 for each k because the level of $\log(\phi^c_{kt})$ is not separately identified from the level of $\log(\omega^c_i)$. Since, by assumption, US firms have not been exposed to the GDPR, this equation identifies the 2-digit industry-specific compute-augmenting productivity trends, denoted $\hat{\phi}^c_{kt}$ in Equation (10). Finally, we also estimate Equation (24) separately for the pre- and post-GDPR periods to report US substitution elasticities by sample period in Figure OA-4.

By Assumption (2), the EU industries follow the same compute-productivity trend as the US industries, so we use the estimated $\hat{\phi}^c_{kt}$ for EU firms.[65] First, we estimate the same equation on the full sample of EU firms to estimate the elasticity of substitution for EU firms. We report these estimates in Table 6. Then, we estimate the same equation using only pre-GDPR data to identify $\hat{\omega}^c_i$ in Equation (10) because there is no distortion before the GDPR. From this estimation, we also estimate the pre-GDPR elasticity of substitution and report them in Figure 4. These first-step estimations provide us with $\hat{\omega}^c_{ik}$ and $\hat{\phi}^c_{kt}$. Using those, we finally estimate Equation (10) in the main text as follows:

$$\log\left(\frac{C_{ikt}}{D_{ikt}}\right) = \gamma_2 + \sigma_2^{EU}\left(\log\left(\frac{p^d_{ikt}}{p^c_{ikt}}\right) + \log(\hat{\phi}^c_{kt})\right) + \sigma_2^{EU}\left(\log(1+\lambda_{ik}) + \log(\hat{\omega}^c_{ik})\right) + \sigma_2^{EU}\log(\eta_{ikt}).$$

by constructing the right-hand side variable. We report σ_2^{EU} as the post-GDPR elasticity of substitution estimates in Figure 4. To estimate the wedge, λ_{ik}, we subtract $\log(\hat{\omega}^c_{ik})$ from the estimated fixed effects in Equation (10) (after accounting for σ_2^{EU}). To account for uncertainty in first-step estimates in standard errors, we follow a bootstrap procedure with 250 repetitions. We resample firms with replacement within each industry separately for US and EU firms, and apply the entire estimation procedure.

We use Equation (11) to estimate the changes in the cost of information, with results reported in Section 6.3. For each estimated $\hat{\omega}^c_{ik}$, we calculate the cost of information by setting λ_{ik} to its estimated value and 0, and then take the difference. This gives us the change in the cost of information due to the GDPR. Since prices and compute-augmenting productivity may change over time, we calculate this change in information cost at every period and report the distribution at the month-firm level in Figure 7(b).

To do the decomposition presented in Equation (6.3), we calculate the cost share of data in the information production cost each period using firms' data input demands and prices. The direct effect is obtained by multiplying data shares with firm-specific wedges.

[65] We also estimate Equation (24) using pre- and post-GDPR data for US firms to separately identify the elasticity of substitution before and after the implementation of GDPR.

The second term (firm re-adjustment) is obtained by subtracting the direct effect from the change in the cost of information. As above, we calculate this change in information cost for each period and report the distribution at the month-firm level.

G.4 Identification Intuition for the Firm-Specific Wedges

Having outlined our estimation strategy in the previous subsection, we now explain how our assumptions help us identify the per-firm wedge in the cost of storing data, λ_i. The main goal is to provide intuition on the variation λ_i is intended to capture. We provide intuition for the case where the elasticity of substitution is the same in the EU and the US (though it may vary pre- and post-GDPR), whereas the more general case offers no additional intuition and requires more cumbersome notation. We consciously abuse notation in this section, as its main goal is to provide simple equations.

Consider two firms in the same industry, one in the EU (k) and one in the US (j), with the same levels of firm-level compute-augmenting productivity $\omega_k^c = \omega_j^c$. For simplicity (to not carry terms around), assume both firms have the same time-varying shocks (i.e., $\log \eta_{kt} = \log \eta_{jt}$ for all t).[66] Subtracting the pre-GDPR first-order condition (Equation 7) of the US firm from the EU firm equation in a period $\underline{t}$ before GDPR implies that:

$$\Delta_i\left(\frac{C_{i\underline{t}}}{D_{i\underline{t}}}\right) = \sigma_1 \Delta_i\left(\frac{p^d_{i\underline{t}}}{p^c_{i\underline{t}}}\right) \tag{25}$$

where we define $\Delta_i(X_{it})$ as the across-firm (EU vs. US) difference in the logarithm of X_{it} at time t (i.e., $\Delta_i(X_{it}) \equiv \log X_{kt} - \log X_{jt}$). Note that Assumption 2 (i.e., EU and US industries follow the same compute augmenting productivity time trend) allows us to get rid of ϕ_t^c if we look at two firms within the same period t. Similarly, by focusing on comparable firms (k and j), we get rid of ω_k^c and ω_j^c.

Analogously, focusing on a period $\bar{t}$ after GDPR was enacted, we can use the post-GDPR identifying equation (Equation 9) in a similar fashion as before (focusing on the same two firms) to obtain:

$$\Delta_i\left(\frac{C_{i\bar{t}}}{D_{i\bar{t}}}\right) = \sigma_2 \Delta_i\left(\frac{p^d_{i\bar{t}}}{p^c_{i\bar{t}}}\right) + \sigma_2 \log(1+\lambda_i) \tag{26}$$

where the extra term is the increase in the cost (λ_i) incurred by the firm in the EU but not by the firm in the US. Subtracting both equations, rearranging terms, and some algebra,

[66] Otherwise, we can work with expectations and use precise (but somewhat cumbersome) notation.

we get:

$$\Delta\Delta_{it}\left(\frac{C_{it}}{D_{it}}\right) = \sigma_2 \Delta\Delta_{it}\left(\frac{p^d_{it}}{p^c_{it}}\right) + (\sigma_2 - \sigma_1)\Delta_i\left(\frac{p^d_{it}}{p^c_{it}}\right) + \sigma_2 \log(1 + \lambda_i) \tag{27}$$

where $\Delta\Delta_{it}(X_{it})$ is the double difference across the EU and US firms and before and after GDPR (i.e., $\Delta\Delta_{it}(X_{it}) \equiv \Delta_i(X_{i\bar{t}}) - \Delta_i(X_{i\underline{t}})$ in our case). These double differences are akin to the ones one would need to generate a difference in difference estimate (e.g., to those in Section 4 of the paper).

Equation (27) provides useful intuition about what λ_i, the post-GDPR wedge, is intended to capture. Loosely speaking, the wedge captures the variation in the shift in the compute intensity (across EU and US firms, before and after GDPR) that is not explained by changes in the shift in the relative prices or by pre-and post-GDPR differences in the elasticity of substitution between compute and storage across comparable EU and US firms.[67] Given the above equation, one would intuitively expect firms that face larger changes in the compute intensity (the negative of the data intensity) to be those that have larger wedges.

Reassuringly, the intuition we outlined above is consistent with our estimated wedges. Recall that we show in the paper that firms became less data-intensive (equivalently, more compute-intensive) after the GDPR. Importantly, we show that industries with greater changes in data intensity exhibit larger wedges. Panel C of Table 4 shows that the changes in the data intensity are smaller (in absolute value) for manufacturing firms, followed by firms in the services industry, and then by software firms. Similarly, our average wedge estimates (shown in Figure 5) have the same ordering: manufacturing firms face smaller wedges, followed by services, and finally by software.

Interestingly, Equations (27) and (26) also show that level changes in C_{it} and D_{it} are not enough to identify λ_i. Note that we cannot infer that firms with larger responses in *levels* would have larger (or smaller) wedges. In fact, to rationalize the level of responses to computing and storage, one would need additional assumptions about the full production function. To explain the responses in levels, we would need to construct a model that incorporates the elasticity of substitution between information and other traditional inputs (e.g., capital and labor).

[67] The more general case that we estimate, where the elasticity of substitution differs between EU and US firms, has a similar intuition but also involves the difference in the changes in σ between the US and the EU, before and after GDPR. We estimate that these differences are not economically important in our context.

H Effects on Production Costs

H.1 The Effect of Changes in Information Costs on Production Costs

In this section, we consider how changes in information costs translate into changes in production costs under various benchmark production function specifications. Per Section 6.4, this exercise aims to derive simple sufficient statistics under various functional form assumptions for the total increase in the cost of producing goods and services arising from the change in the cost of data storage. As such, we leverage the assumption that firms face linear prices (p) for all inputs. Thus, the resulting variable cost function is given by:

$$VC\left(\bar{Y}, p, \Delta CI\right) = p_L L^*\left(\bar{Y}, p, \Delta CI\right) + p_K K^*\left(\bar{Y}, p, \Delta CI\right) + p_I I^*\left(\bar{Y}, p, \Delta CI\right).$$

where we use $\bar{Y}$ throughout the section to denote the quantity of production, and where ΔCI is the percentage increase in the information cost.

We first consider two edge cases—Leontief and linear production functions—where information is a perfect complement and a substitute for other inputs. These provide us with intuitive bounds for how changes in the costs of information might translate into production costs. Next, we consider an intermediate case with Cobb-Douglas production technology and derive a simple equation for how changes in information costs translate into production costs after firms re-optimize between inputs. Finally, we analyze a nested CES with information and non-information inputs.

Leontief Production Function

We first consider the simple case of a Leontief production function, where inputs must be combined in fixed proportions:

$$Y = \min\left(\frac{L}{\alpha}, \frac{K}{\beta}, \frac{I}{\gamma}\right).$$

Cost minimization immediately implies that for any given level of production, the input demand functions are given by:

$$L^* = \alpha\bar{Y}, \qquad K^* = \beta\bar{Y}, \qquad I^* = \gamma\bar{Y}.$$

In this case, the cost function is therefore linear in prices, and a ΔCI percentage increase in the cost of information causes an $\Delta CI \cdot s^I_{it}$ percentage increase in the cost of production.

Linear Production Function

The case of a linear production function is straightforward, as firms simply choose the most cost-effective input or mix between them if they are equally cost-effective.

$$Y = \alpha L + \beta K + \gamma I.$$

In the interior case where firms were previously producing with non-zero capital or non-zero labor, cost minimization immediately implies that a ΔCI percentage increase in the cost of information translates into a zero percentage increase in the cost of production.

Cobb-Douglas Production Function

Next, we consider the effects of a ΔCI percentage increase in the cost of information for a Cobb-Douglas production function given by

$$Y = L^{\alpha} K^{\beta} I^{\gamma}$$

where the production function is constant returns to scale $(\alpha + \beta + \gamma) = 1$, First-order conditions imply the following information demand function:

$$I^* = \bar{Y}^{\frac{1}{\gamma+\alpha+\beta}} \cdot \left(\frac{p^I}{\gamma}\right)^{\frac{-\alpha-\beta}{\gamma+\alpha+\beta}} \cdot \left(\frac{\beta}{p^K}\right)^{\frac{-\beta}{\gamma+\alpha+\beta}} \cdot \left(\frac{\alpha}{p^L}\right)^{\frac{-\alpha}{\gamma+\alpha+\beta}}$$

This immediately implies that a ΔCI percentage increase in p^I induces a $\delta = \left[(1+\Delta CI)^{-\frac{\alpha+\beta}{\gamma+\alpha+\beta}} - 1\right]$ percentage decrease in I^*.[68] Next, we note that first-order conditions imply that a γ share of total firm costs will be spent on information:

$$\gamma = \frac{p^I \cdot I^*\left(\bar{Y}, p, \Delta CI\right)}{E\left(\bar{Y}, p, \Delta CI\right)}.$$

Using the change in information expenditure resulting from the ΔCI increase in information prices and the δ decrease in I^* derived above, we have that a ΔCI percentage increase in p^I will lead to a ΔVC percentage increase in production costs, where $\Delta VC = (1+\Delta CI)^{\gamma} - 1$.[69]

[68] For marginal changes, using log transformations and taking derivatives yields $\frac{\partial \log I}{\partial \log p^I} = \frac{\alpha+\beta}{\gamma+\alpha+\beta}$.

[69] Once again using log transformations and taking derivatives yields the intuitive expression $\frac{\partial \log(E)}{\partial \log(p^I)} = 1 - \frac{\alpha+\beta}{\gamma+\alpha+\beta}$ for marginal changes from $\Delta CI = 0$.

CES Production Function

Finally, we consider a simple nested constant elasticity of substitution production technology, where information I is combined with a constant returns to scale aggregator of all non-information inputs $M(L, K)$. We denote the outer nest by

$$Y_i = \nu_i \left(\beta_i I_i^{\bar{\rho}} + (1 - \beta_i) M_i^{\bar{\rho}} \right)^{1/\bar{\rho}}.$$

where ν_i represents firm-specific productivity, β_i represents firm-specific information intensity in production, and $\bar{\sigma} = 1/(1 - \bar{\rho})$ denotes the elasticity of substitution between information and non-information inputs. Moving forward, we will drop the firm-specific subscripts for notational simplicity.

Next, we note that because $M(L, K)$ exhibits constant returns to scale, the linear prices of labor and capital – p_L and p_K – imply a linear unit cost for the intermediate non-information aggregate M. We denote that unit cost by p_M.[70] This, therefore, yields the unit cost function

$$c(p_I, p_M) = \frac{1}{\nu} \left(\beta^{\bar{\sigma}} (p_I)^{1-\bar{\sigma}} + (1 - \beta)^{\bar{\sigma}} (p_M)^{1-\bar{\sigma}} \right)^{\frac{1}{1-\bar{\sigma}}}.$$

Now, denote the equilibrium information expenditure share as $s_I^* \equiv \frac{p_I \cdot I}{p_M \cdot M + p_I \cdot I}$. Combining this with the first-order conditions allows us to express this term as

$$\frac{s_I^*}{1 - s_I^*} = \left(\frac{p_I}{p_M} \right)^{1-\bar{\sigma}} \left(\frac{\beta}{1 - \beta} \right)^{\bar{\sigma}}.$$

Finally, we can use this equivalence to express the effects of a ΔCI percentage increase in p_I on production costs using only model parameters and s_I^*:

[70] Deriving the formula for the unit cost of M yields $p_M = \frac{1}{\tau} \left(\kappa^{\sigma_{kl}} p_L^{(1-\sigma_{kl})} + (1 - \kappa)^{\sigma_{kl}} p_K^{(1-\sigma_{kl})} \right)^{1/(1-\sigma_{kl})}$ where κ is the labor share parameter, τ is a scaling constant, and σ_{kl} denotes the elasticity of substitution between capital and labor.

$$\begin{aligned}\frac{c\big((1+\Delta CI)p_I, p_M\big)}{c\left(p_I, p_M\right)} &= \left(\frac{(1+\Delta CI)^{1-\bar{\sigma}}\beta^{\bar{\sigma}}p_I^{1-\bar{\sigma}} + (1-\beta)^{\bar{\sigma}}p_M^{1-\bar{\sigma}}}{\beta^{\bar{\sigma}}p_I^{1-\bar{\sigma}} + (1-\beta)^{\bar{\sigma}}p_M^{1-\bar{\sigma}}}\right)^{\frac{1}{1-\bar{\sigma}}} \\ &= \left(\frac{(1+\Delta CI)^{1-\bar{\sigma}}\left(\frac{\beta}{1-\beta}\right)^{\bar{\sigma}}\left(\frac{p_I}{p_M}\right)^{1-\bar{\sigma}} + 1}{\left(\frac{\beta}{1-\beta}\right)^{\bar{\sigma}}\left(\frac{p_I}{p_M}\right)^{1-\bar{\sigma}} + 1}\right)^{\frac{1}{1-\bar{\sigma}}} \\ &= \left((1+\Delta CI)^{1-\bar{\sigma}}s_I^* + 1 - s_I^*\right)^{\frac{1}{1-\bar{\sigma}}}.\end{aligned}$$

Thus, a ΔCI percentage increase in p_I yields a $\left((1+\Delta CI)^{1-\bar{\sigma}} \cdot s_I^* + 1 - s_I^*\right)^{\frac{1}{1-\bar{\sigma}}} - 1$ percentage increase in production costs.

H.2 Estimating Key Parameters of Production Cost Increases

We show in the section above that the information share of expenditure is crucial to calculating how an increase in the cost of information translates to production costs. In the nested CES production technology we analyzed above, the vector with the elasticity of substitution between information and non-information inputs and the information cost share is a sufficient statistic for this effect. We discuss estimates of both parameters below.

First, we combine various data sources to suggest a reasonable range for the information cost share. We provide these estimates in Table OA-11. Next, we discuss each of those data sources separately. Finally, we discuss mapping estimates from Lashkari et al. (2024) of the elasticity of substitution between IT and non-IT inputs into our setting.

Aberdeen

We begin by turning to the Aberdeen data set, which we discuss in Section 3.2 and in Appendix C.3. The Aberdeen data provides estimates of site-level IT spending and revenue, which we collapse to the firm level. Unfortunately, we are unable to directly observe total firm expenditures; therefore, we proxy for them with firm revenue. A revenue-based measure would be equivalent to a cost-based measure under the assumptions of perfect competition and constant returns to scale. Although these assumptions are strong, we adopt them to obtain back-of-the-envelope estimates of production costs. We construct the average share of IT revenue spent by European and US firms in 2017 and 2018 by three primary industries of interest: software, services, and manufacturing. We find that, somewhat unsurprisingly, software firms allocate the largest share of their revenue to IT,

Table OA-11: Estimates for the Information Share of Expenditure by Industry

	Software (1)	Services (2)	Manufacturing (3)
	Aberdeen Estimates		
Aberdeen (EU 2017)	16.7%	3.7%	3.3%
Aberdeen (EU 2018)	14.9%	2.9%	2.9%
Aberdeen (US 2017)	8.7%	4.9%	3.0%
Aberdeen (US 2018)	8.7%	5.0%	3.2%
	Survey Estimates		
Flexera (2020)	24.7%	6.7%	4.1%
Gartner (2022)	7.1%	5.4%	2.3%
Computer Economics (2019)	–	–	1.4% - 3.2%

Notes: Table presents estimates for the information share of expenditure by industry. All estimates are formed by calculating or observing the average share of firm revenue spent on IT. Column (1) presents these estimates for software firms, which are defined in the Aberdeen data through SIC codes 7370 - 7377. Column (2) presents estimates for firms in services. Column (3) presents estimates for manufacturing firms. Further details on the Aberdeen data and the survey estimates are provided in Appendix H.2.

followed by services and manufacturing.

Industry Surveys

Next, we use industry surveys as supportive evidence that the ranges suggested by Aberdeen data are reasonable. These surveys include Flexera, Gartner, and Computer Economics. These are specifically Flexera's *2020 State of Technology Spending Report*, Gartner's *IT Key Metrics Data 2023: Industry Measures — Insights for Midsize Enterprises*, and Computer Economics's *2019 IT Spending & Staffing Benchmarks – Executive Summary*. For the Flexera survey, we use the "industrial products" industry estimate as the manufacturing estimate, and for the Gartner survey, we take the "professional services" industry estimate as our estimate for non-software service firms. While the samples and industry definitions vary widely across these surveys, the numbers cited are generally consistent with the ranges suggested by Aberdeen.

IT Expenditure Data from the Bureau of Economic Analysis

While the previous sources rely on revenue shares due to data limitations, we now turn to data sources that report industry-level IT expenditures from the Bureau of Economic Analysis (BEA) and total expenditures from the US Census, and combine them to obtain IT expenditure shares for our industries. The first row of Table OA-12 reports industry-

level IT capital investments in 2017, expressed as shares of total business expenses. We also report, in the second row, IT expenditures as a share of total revenue for comparison purposes.

The IT expenditures data come from the BEA *Detailed Fixed Assets* table, which reports annual investment flows in private non-residential fixed assets by industry and NIPA asset type. We define IT capital as investment in the following types of assets: (i) Capitalized Software (Prepackaged, Vendor Customized, Internally Developed); (ii) Computer and Peripheral Equipment; and (iii) Information and Communication Technology Equipment, Excluding Computers and Peripherals. We aggregate the BEA industry series to the three industry groupings (manufacturing, services, and software) to obtain total IT capital expenditures in 2017 for each industry. The shares in Table OA-12 are computed as IT investment divided by the corresponding 2017 industry revenue or total business expenses.

For these measures, Manufacturing is defined as NAICS 31–33. Services are defined as NAICS 51–81. The software sector is proxied by NAICS 51 (Information). Revenue and expense data for manufacturing are taken from the Annual Survey of Manufacturers (ASM) at NAICS 31–33. The corresponding revenue and expense series for services and software are taken from the Service Annual Survey (SAS), aggregated to NAICS 51–81 for services and restricted to NAICS 51 for software.

Table OA-12: IT Capital Expenditure Shares by Industry

	Software (1)	Services (2)	Manufacturing (3)
IT Capital Share of Business Expenses	14.5%	5.7%	2.8%
IT Capital Share of Revenue	10.8%	3.7%	1.9%

Notes: Table presents IT capital expenditure shares by industry for 2017. IT capital expenditure data are from the Bureau of Economic Analysis (BEA) Detailed Fixed Assets tables. Revenue and business expense data for the manufacturing sector are from the Annual Survey of Manufactures (ASM) with NAICS 31-33. Revenue and business expense data for the service and software sectors are from the Service Annual Survey (SAS). Column (1) presents estimates for software firms, defined as NAICS code 51 (Information). Column (2) presents estimates for services, defined as NAICS codes 51-81. Column (3) presents estimates for manufacturing firms, defined as NAICS 31-33.

Estimates of the Elasticity of Substitution between IT and Non-IT Inputs

We use point estimates of the elasticity of substitution between IT and non-IT inputs from Lashkari et al. (2024) to proxy for the elasticity of substitution between information and non-information inputs. We focus on the micro-elasticities provided in the text rather than

the macro-elasticities, which reflect general equilibrium forces and reallocation between firms. We use their industry-level elasticities from a non-homothetic CES specification. Estimates for the manufacturing industry are provided directly. We map the "information and communication technology" industry to software, and we construct an estimate for the elasticity in services by taking a weighted average of the relevant industries for which estimates were provided in the online appendix.

Estimates of the Contribution to GDP by Industry and GDP in the EU Area

To measure each industry's contribution to GDP, we use the information provided by OECD (2020) for the Euro Area using their output approach outlined on page 189. We measure the manufacturing contribution to GDP as the manufacturing output at basic prices (line 4), divided by the total gross value added at basic prices (line 1), and get 16.9%. To measure software and non-services, we use a two-step approach. We first compute the service contribution to GDP by summing all of the service industries in the OECD table (lines 6 to 12) and dividing it by the total gross value added (line 1) to get 73.4%. We then separate into "software" and "non-software" by estimating the share of the software industry as a proportion of the service industry.

To separate these industries, we use data from the U.S. Census to compute the software industry's share of the service sector, as we could not find reliable estimates for the EU. To compute this, we use the 2019 SUSB Annual Data Tables by Establishment Industry provided by the US Census Bureau. We compute the software industry share by dividing employment in the software industry by the total employment in the service industry and get 6.9%.[71] We use this number to proxy for the EU size of the software industry.

Finally, we return to OECD (2020) to measure total GDP for the EU area and use their 2018 estimate (line 64 on p. 189), which is €11.5 trillion.

[71] To do this, we map from SIC to NAICS codes using Orbis data and assign each service industry code as "software" or "non-software" to match the definitions used in the paper.

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