The Impact of the General Data Protection Regulation (GDPR) on Online Usage Behavior

Klaus M. Miller¹, Julia Schmitt, Bernd Skiera

Klaus M. Miller, Assistant Professor of Marketing, HEC Paris, Rue de la Libération 1, 78350 Jouy-en-Josas, France, Hi!PARIS Chairholder, Center in Data Analytics & AI for Science, Technology, Business & Society, Phone +33-1-39-67-70-88, millerk@hec.fr.

Julia Schmitt, Department of Marketing, Faculty of Economics and Business, Goethe University Frankfurt, Theodor-W.-Adorno-Platz 4, 60323 Frankfurt, Germany, Phone +49-69-798-34563, Email: schmitt@wiwi.uni-frankfurt.de.

Bernd Skiera, Professor of Electronic Commerce, Department of Marketing, Faculty of Economics and Business, Goethe University Frankfurt, Theodor-W.-Adorno-Platz 4, 60323 Frankfurt, Germany, Phone +49-69-798-34649, skiera@wiwi.uni-frankfurt.de); also Professorial Research Fellow at Deakin Business School, 221 Burwood Highway, Burwood, VIC 3125, Australia (bernd.skiera@deakin.edu.au).

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¹ Corresponding author.

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ABSTRACT

Privacy regulations often necessitate a balance between safeguarding consumer privacy and preventing economic losses for firms that utilize consumer data. However, little empirical evidence exists on how such laws affect firm performance. This study aims to fill that gap by quantifying the impact of the European Union's General Data Protection Regulation (GDPR) on online usage behavior over time. We analyzed data from 6,286 websites across 24 industries, covering 10 months before and 18 months after the GDPR's enactment in 2018. Employing a generalized synthetic control estimator, we isolated the short- and long-term effects of the GDPR on user behavior. Our results show that the GDPR negatively affected online usage per website on average; specifically, weekly visits decreased by 4.88% in the first 3 months and 10.02% after 18 months post-enactment. At the 18-month mark, these declines translated into average revenue losses of about \$7 million for e-commerce websites and nearly \$2.5 million for ad-based websites. Nonetheless, the GDPR's impact varied across website size, industry, and user origin, with some large websites and industries benefiting from the regulation. Notably, the largest 10% of websites pre-GDPR suffered less, suggesting that the GDPR has increased market concentration.

Keywords: Economics of Privacy, Public Policy, Consumer Protection, Synthetic Control, Difference in Differences, Quasi Experiments

Internet users are increasingly concerned about their privacy online. Policymakers worldwide have enacted privacy laws to address these concerns (Jin and Skiera 2022). While the specifics of these laws vary, they share a fundamental goal: to enhance individuals' control over their personal data (Westin 1967). One of the most stringent laws is the General Data Protection Regulation (GDPR), which the European Union enacted on May 25, 2018.

The GDPR has led to several intended outcomes. Notably, it has reduced the use of third-party cookies (Libert et al. 2018) and the number of web technology vendors on websites (Johnson et al. 2023; Peukert et al. 2022). Websites have also improved their privacy policies by incorporating more comprehensive information (Degeling et al. 2019; Linden et al. 2020; Warberg et al. 2023). However, the GDPR may have also triggered unintended effects. The decrease in data collection could result in revenue losses for firms (Wang et al. 2024), potentially leading to job cuts and financial hardships for employees. Companies might scale back services or introduce fees for previously free offerings to compensate for these losses, which could negatively impact society.

Therefore, we aim to derive the effect of GDPR on online usage behavior and decompose it into a quantity effect (e.g., the number of unique visitors) and an intensity effect (e.g., visits per unique visitor).

Regarding user quantity, limitations on data collection and usage restrict firms' marketing activities, such as targeting new customers through personalized ads. As a result, users might be less aware of certain firms and face increased search costs to find them, potentially decreasing traffic to their websites. Conversely, users with fewer alternatives may concentrate their attention on a few well-known websites, increasing traffic to those sites. Indeed, shortly after GDPR, some non-EU websites blocked access to EU users to avoid compliance (Lecher 2018). Additionally, some users might abandon websites to prevent sharing their data.

Regarding usage intensity, the GDPR's requirements for transparency and consent may compel websites to adjust their appearance, affecting the user experience (Hils et al. 2020). For example, users might encounter a pop-up with information about a website's cookie usage or data collection

practices and need to accept or decline these terms. This interaction might increase users' awareness of data disclosure and influence their usage intensity (Dinev and Hart 2006). Users might spend less time on a website to reduce the data it collects. Alternatively, once users have consented to data collection, they might use the website more than before to avoid visiting other sites and authorizing additional data collection. This behavior aligns with the sunk-cost-effect, where users prefer websites to which they have already provided data (Arkes and Blumer 1985). Lastly, some users might not change their behavior at all.

These arguments suggest that enacting a privacy law such as GDPR may have positive, negative, or negligible effects on online usage behavior and the underlying user quantity and usage intensity of particular websites. Moreover, the effects might differ across websites. Users' privacy expectations and responses to privacy-driven changes in website operations may vary across countries (reflecting cultural differences) or industries (Dinev et al. 2006). The effects could also evolve, as users may take several months to adjust their usage habits (Acquisti 2024).

Given these potential risks, policymakers must carefully balance citizens' right to privacy against the performance of firms that rely on user data and the potential societal effects of firms' lost income. However, predicting how implementing privacy laws will affect firms' performance is challenging. Part of the challenge stems from users responding unexpectedly to efforts to protect their privacy. Indeed, although users claim to value their privacy, their actual online behavior does not always align with their stated preferences—a phenomenon known as the privacy paradox (Acquisti 2004).

To better understand the actual impact of such a law, we conducted an empirical study of how the GDPR's enactment on May 25th, 2018, affected online usage behavior on thousands of websites. We focus on overall online usage behavior and decompose it into two classes of usage behavior metrics: user quantity (e.g., unique visitors) and usage intensity (e.g., visits per unique visitor). These metrics are crucial indicators of firm performance and often link with firms' revenues, particularly for e-commerce sites and sites with ad-based revenue (as discussed in the paper's concluding sections).

Specifically, we set out to:

- 1) **Quantify the effect of GDPR** on two usage behavior metrics—namely weekly visits and page impressions— over time (from 3 up to 18 months post-GDPR);
- 2) Understand the mechanism behind these two metrics by decomposing each into one user quantity metric and one usage intensity metric over time (from 3 up to 18 months post-GDPR);
- Identify how these effects vary across website characteristics (i.e., website industry and size) and users' country of origin.

Our analysis relies on a dataset capturing usage behavior on 6,286 unique websites spanning 24 industries, comprising the most popular websites in 13 developed countries (11 EU countries, Switzerland, and the United States). The data cover the period from July 2017 through December 2019—i.e., 10 months before and 18 months after the GDPR's enactment (hereafter referred to as "GDPR") on May 25th, 2018—enabling us to construct a before-and-after analysis. Within our dataset, some website–user interactions are subject to the GDPR (i.e., interactions involving EU websites or EU users), while others are not (i.e., interactions involving non-EU websites and non-EU users). The latter serves as a control group. We use a generalized synthetic control (GSC) estimator (Xu 2017) to isolate the effect of GDPR on our metrics of interest. We discuss and provide robustness tests to support our assumptions for estimating GDPR's effect.

We derive the following results:

 Overall Decrease in Usage Behavior: Among websites to which GDPR is applicable, usage behavior—as measured by the average weekly visits per website—decreased by 4.88% in the short-term (3 months post-GDPR) and 10.02% in the long-term (18 months post-GDPR). For page impressions, we observed similar decreases of 3.12% at 3 months post-GDPR and 9.28% at 18 months post-GDPR.

- 2) Decomposition of Effects: Decomposing the effect of the GDPR on visits helps understand the mechanism behind the GDPR effect, as visits are the product of unique visitors and average visits per visitor. Two factors could drive the decrease in visits: First, unique visitors decreased by 0.77% at 3 months post-GDPR and by 6.61% 18 months post-GDPR. Second, the remaining unique visitors also decided to return less frequently to the websites they visit, as indicated by a 1.62% decrease in the average visits per unique visitor at 3 months post-GDPR. At 18 months post-GDPR, the reduction of average visits per unique visitor becomes weaker (0.59%).
- 3) Variation Across Websites: The effect of the GDPR varied across websites. More than half of the websites (54.87%) continued to experience a decrease in visits 18 months post-GDPR, while about one-quarter of the websites (23.96%) showed an increase in visits and thus even benefitted from the GDPR. Among websites that lost unique visitors post-GDPR (i.e., experienced a decrease in user quantity), the remaining users exhibit an increase in usage intensity—for example, visits per unique visitor increased, on average, by 4.77% at 18 months post-GDPR. Conversely, usage intensity decreased among websites that gained unique visitors post-GDPR; e.g., visits per unique visitor decreased, on average, by 9.09% at 18 months post-GDPR. The smallest 10% of websites pre-GDPR lost more weekly visits post-GDPR (from 13.89% at 3 months post-GDPR to 21.49% at 18 months post-GDPR) than the largest 10% of websites pre-GDPR to 9.04% at 18 months post-GDPR), suggesting that GDPR increased market concentration.
- 4) Industry-Specific Effects: The effects varied across industries. GDPR negatively affected
 'Heavy Industry and Engineering' after 18 months post-GDPR (-44.76%), followed by 'Health'
 (-15.15%) and 'Computer, Electronics and Technology' (-14.80%). By contrast, websites in the

categories 'Vehicles' and 'Community and Society' experienced positive effects (increases of 3.85% and 4.69% after 18 months post-GDPR, respectively).¹

5) Country-Specific Effects: Finally, the effects of GDPR varied by the user's country of origin. Websites whose primary users were from Poland, Germany, or Denmark suffered the least from GDPR, with a decrease in weekly visits per website 18 months post-GDPR of -5.55%, -6.55%, and -6.97%, respectively. The most substantial drops after 18 months occurred for users from the Netherlands (-17.20%), Sweden (-13.36%), and the UK (-12.57%).

EFFECTS OF PRIVACY CHANGES ON ONLINE USAGE BEHAVIOR

Two main streams of literature study the effects of privacy changes on online usage behavior. The first stream attempts to illuminate users' attitudes and behavior toward privacy and their responses to different levels of privacy or control over their data through lab experiments and surveys. The second stream uses field studies and quasi-experiments to examine the effects of privacy laws on various outcomes of interest.

Users' Attitudes and Behavior Regarding Privacy

Laboratory experiments and survey-based studies have examined how websites' handling of user privacy affects users' attitudes and behavior, revealing a nuanced relationship between privacy and usage behavior. Several studies suggest that when users perceive themselves as having more control over their privacy—specifically, more options to regulate their privacy—they experience less concern about privacy (Martin 2015), exhibit higher levels of trust in a website, show increased purchase intentions (Martin et al. 2017), and display a greater willingness to disclose data to

 ¹ Example websites for the industry categories are: 'Heavy Industry and Engineering': Energy de France (www.edf.fr).
 'Health': Doctolib (www.doctolib.de). 'Computer Electronics and Technology': Google (www.google.com).
 'Vehicles': Tesla (www.tesla.com). 'Community and Society': Tinder (www.tinder.com).

websites (Brandimarte et al. 2013; Acquisti et al. 2013; Malhotra et al. 2004; Culnan and Armstrong 1999). They may even react more positively to personalized ads (Tucker 2013).

Conversely, other studies find that varying levels of privacy do not significantly affect usage behavior. For example, Bélanger and Crossler (2011) demonstrate that users share data with firms despite privacy concerns, perhaps because they feel powerless to protect their privacy (Few 2018). Acquisti et al. (2012) further show that user privacy concerns and preferences are contextdependent; the willingness to disclose data can depend on situational factors, such as the amount and order of such information requests. These findings align with the privacy paradox, indicating that users' stated privacy preferences often differ from their actual behavior (e.g., Acquisti 2004).

Some studies even suggest that providing more privacy control options to users may negatively affect online usage behavior. Privacy features —such as requests for users' explicit consent for data collection— can heighten users' awareness of data disclosure (Dinev and Hart 2006). This increased awareness may elevate privacy concerns, reduce ad effectiveness (Kim et al. 2018), make users more wary about using the site, and lead them to use it less frequently.

Dinev and Hart (2006) proposed the privacy calculus theory, which offers a framework encompassing these different responses to privacy controls. This theory suggests that the extent to which a user values privacy on a particular website depends on the user's privacy concerns, trust in the website, and the value derived from the website's offerings. Users with significant privacy concerns or lower trust in a website are more likely to respond favorably to stringent privacy measures. In contrast, users who value the website's offerings may sacrifice their privacy in exchange for access. Therefore, they may be indifferent to the level of privacy offered and may even respond unfavorably if privacy safeguards reduce the website's accessibility.

The privacy calculus theory implies that responses to changes in a website's privacy handling may vary by user and website. Indeed, several studies show that privacy perceptions and expectations depend on a user's country and cultural background (e.g., Dinev et al. 2006; Steenkamp and Geyskens 2006; Miltgen and Peyrat-Guillard 2014). The current study extends these findings by comparing how users in different countries vary in their responses to GDPR and by considering variations across websites with different characteristics.

Effects of Privacy Laws on Various Outcomes

The findings above suggest that predicting how large populations of users will respond to the GDPR is challenging. Accordingly, several studies have utilized field data as quasi-experiments to construct event studies of users' revealed behavior following the enactment of such laws. For example, prior to the GDPR, Goldfarb and Tucker (2011) demonstrated that implementing the EU Privacy and Electronic Communications Directive reduced ad effectiveness on websites, making it more difficult for ad-financed websites to generate revenues. Campbell et al. (2015) showed that privacy laws disproportionately hurt smaller online firms than larger ones.

More recent studies have sought to characterize the effect of GDPR on various outcomes (see Johnson 2023 and Goldfarb and Que 2023, for overviews). The GDPR led to an apparent reduction in third-party cookies (Libert et al. 2018; Lefrere at al. 2024) and a decrease in web technology vendors (Johnson et al. 2023; Peukert et al. 2022). Anticipating this reduction, Mirreh (2018) predicted that websites could eventually lose almost half of their traffic due to the inevitable shifts in retargeting strategies, making it more challenging for firms to attract users. Other research focuses on websites' actions in response to the law, showing that many updated their privacy policies (Degeling et al. 2019), increased the length of these policies (Linden et al. 2020), and reduced the number of nudges encouraging users to accept tracking (Warberg et al. 2023).

In Table 1, we summarize three related empirical studies. Lefrere et al. (2024) examine the impact of the GPDR on online content providers and find a small reduction in page impressions per visitor on news and media websites in the EU relative to US websites, but no significant impact on new content provision and social media engagement. In contrast, Zhao et al. (2023) document increased online search intensity post-GDPR, indicating that users may face a more challenging online environment after the regulation's introduction.

Closest to our research is a complementary study by Goldberg et al. (2024), who measured how the GDPR affected web traffic and e-commerce sales of websites. While Goldberg et al. (2024) determined a short-term effect— 4 months post-GDPR—using a selected sample of 1,084 websites that adopted Adobe Analytics, our study adopts a long-term perspective of up to 18 months post-GDPR. We analyze a substantially larger sample of 6,286 websites spanning 24 industries to facilitate a more comprehensive analysis of the GDPR. Our study encompasses over 1.15 trillion website visits from the EU and 1.8 trillion from Switzerland and the US during our observation period.

Goldberg et al. (2024) used a difference-in-differences (DID) estimator to identify the effect of the GDPR, treating websites with EU users as the treatment group and observations from the same websites in the previous year as the control group. This identification strategy assumes that the control group shares seasonal trends and characteristics with the treatment group.

In contrast, we employ a generalized synthetic control (GSC) estimator to identify GDPR's effect on EU websites and websites with EU users as the treatment group (see Figure 1), using non-EU websites with non-EU users as the control group. Our identification strategy allows us to observe treatment and control websites pre- and post-GDPR. However, given the GDPR's broad scope, we did not have a direct control website for every treatment website and thus relied on the GSC estimator to construct a suitable control group.

Study		Goldberg et al. (2024) American Economic Journal	Lefrere et al. (2024) Working Paper	Zhao et al. (2023) Working Paper	This Study Working Paper	
Aim of Study		Effect of GDPR on page impressions and revenue of affected websites in EU	Effect of GDPR on affected online content providers in EU	Effect of GDPR on online search behavior of affected EU users and websites	Effect of GDPR on affected online user behavior in EU and US, and variation across websites and users	
Effect of GDPR		Negative effect	Negative effect	Negative effect	Negative and positive effect	
Duration of Effect	Short-term	Yes (4 months)	No	No	Yes (3 and 6 months)	
of GDPR	Long-term	No	Yes (17 months)	Yes (14 months)	Yes (9, 12, and 18 months)	
Heterogeneity of Effect of GDPR	Websites	No	No	No	Yes	
across	Users	No	No	No	Yes	
Separation of Web Traffic from EU users and non-EU users		No	No	No	Yes	
Main Method		Panel Differences Estimator	Difference-in-Differences Estimator	Generalized Synthetic Control Estimator	Generalized Synthetic Control Estimator	
Data Source for User Behavior Metrics		Adobe Analytics	Alexa	Netquest	SimilarWeb, AGOF	
Unit of Analysis		Website-week-level	Website-week-level	User-week-level, Website-week-level	Website-instance-week-level	
Observation Period		January – September 2017 January – September 2018 (18 months)	April 2017 – November 2019 (32 months)	January 2018 – September 2019 (21 months)	July 2017 – December 2019 (30 months)	
Number of Observations		69,344	13,624	1,125,456	1,268,473	
Online Usage		Yes (Visits, Page Impressions)	Yes (Page Impressions)	Yes (Page Impressions)	Yes (Visits, Page Impressions)	
User Behavior Metrics	User Quantity	Yes (Visits)	Yes (Unique Visitors)	No	Yes (Unique Visitors, Visits)	
	Usage Intensity	No	Yes (Page Impressions per Unique Visitor)	No	Yes (Visits per Unique Visitor, Page Impressions per Visit)	

Table 1:Comparison of Empirical Studies on the Impact of GDPR on Online User Behavior

Finally, Goldberg et al. (2024) used Adobe data on recorded user behavior and several assumptions to determine GDPR's effect on actual user behavior. Our study utilizes estimated user behavior data from SimilarWeb, aligning with methodologies in other GDPR studies. For example, Peukert et al. (2022, Web Appendix 2.2 (p. 4-5)) study the impact of GDPR on web technology vendors using user panel data from whotracks.me, and Leferere et al. (2024) use data from Alexa to investigate the regulation's impact on online content providers. SimilarWeb combines user panel data, website analytics data and other sources to account for non-consenting users post-GDPR. This approach is similar to how Google Analytics now accounts for non-consenting users due to the GDPR². Our data enable empirical estimation of metrics covering online usage behavior, which does not differ in a statistically significant way from uncensored "ground truth" data (see Web Appendix F). As Goldberg et al. (2024) noted, the change in recorded user behavior post-GDPR was a combination of two factors: a change in the number of consenting users and a change in the actual behavior of these consenting users. Since SimilarWeb controls for measurement error due to non-consenting users post-GDPR, we measure the impact of GDPR on actual online usage behavior.

DESCRIPTION OF EMPIRICAL STUDY

Our empirical study aims to analyze the effect of the GDPR on online usage behavior and to understand how these effects evolve, distinguishing between short-term effects within the first 3 months and the long-term effects up to 18 months after the GDPR. Furthermore, we investigate how these effects vary as a function of website and user characteristics.

² https://www.searchenginejournal.com/google-analytics-will-track-data-without-cookies/407030/.

Background on GDPR

The GDPR, enacted by the EU on May 25th, 2018, is Europe's first major privacy law since the e-Privacy Directive of 2002. The statute regulates any activity performed on personal data from users located in the EU. Article 3 of the GDPR states that the law is binding for all websites based in EU countries and applies if a website's data processing occurs in Europe. Websites that fall under GDPR but do not comply with the privacy law face significant fines of up to 4% of the website's global annual turnover or €20 million, whichever is higher.

Description of Set-Up of Empirical Study

Our empirical study examines the effect of the GDPR's enactment on usage behavior across various websites. Before the GDPR, users could not anticipate how websites would react to the diverse GDPR requirements. Post-GDPR, we observe users' subsequent reactions to websites' interpretations of the GDPR. This approach corresponds to measuring the intention-to-treat effect of the GDPR. In other words, we assess GDPR's effect on treatment websites regardless of whether these websites complied with the regulation.

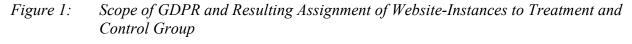
As in other studies on the GDPR that use non-EU users as a control group (Jia et al. 2021; Zhuo et al. 2021), our control group comprises websites without an intention-to-treat. However, some control websites may have been indirectly affected due to voluntary compliance with the GDPR—a phenomenon we refer to as the spillover effect.

Measuring the effect of the GDPR's enactment is policy-relevant as it allows us to gauge the consequences of introducing such a privacy law. This effect differs from the enforcement effect of the GDPR, which would be the effect if all treatment websites complied with the regulation and all control websites did not. For conceptual clarity, we reserve the term "enforcement" for cases where, for example, data protection authorities actively enforce the law by imposing fines.

Our estimate of the GDPR's enactment may thus include the interpretation of both the treated and untreated control websites and users' subsequent reactions to GDPR. If a spillover effect from the treatment to the control websites is present, our measurement reflects the differential effect of the GDPR on the treatment websites, including the spillover effect. As we discuss in the identifying assumptions below, such a spillover effect may exist 3 months post-GDPR but diminishes 18 months post-GDPR. Even if it exists, our supplementary analyses suggest that the spillover effect is limited in magnitude, leading us to underestimate the impact of GDPR.

The GDPR provides a useful setting for quantifying the effect of a privacy law on online usage behavior because it divides website–user interactions (here referred to as "observations") into a treatment group (where the GDPR is applicable) and a control group (where the GDPR is inapplicable), as depicted in Figure 1. As noted above, GDPR's scope includes all websites based in the EU and personal data collected from all users in the EU. Thus, the treatment group comprises observations corresponding to EU users visiting any website (Cells 1 and 3 in Figure 1) or non-EU users visiting EU websites (Cell 2 in Figure 1). The control group consists of observations corresponding to non-EU users visiting non-EU websites (Cell 4 in Figure 1). In line with Article 3 of GDPR, we use the website's server location (retrieved from https://check-host.net) to determine the respective website's data processing location and GDPR's applicability.

We use the enactment date of GDPR (May 25th, 2018) to construct a before-and-after analysis, comparing the treatment group to the control group to quantify GDPR's effect. This approach allows us to construct a GSC estimator (Xu 2017) that rests upon several critical assumptions, which we outline below.



		Base of User
		EU Non-EU
Base of	EU	GDPR applies = Treatment Group (Cell 1)GDPR applies = Treatment Group (Cell 2)
Website	Non-EU	GDPR applies = Treatment Group (Cell 3)GDPR does not apply = Control Group (Cell 4)
		Treatment Group Control Group

Overview of Data

Description of sample. This study utilizes data from SimilarWeb for the top 1,000 websites—as listed in Alexa Top Sites in April 2018—of two non-EU countries (Switzerland and the United States) and 11 EU countries (Austria, Denmark, France, Germany, Hungary, Italy, Netherlands, Poland, Spain, Sweden, and the UK³). We chose the United States and Switzerland because both countries are culturally similar to the EU. SimilarWeb draws on a diversified and rich global user panel to measure online usage behavior. The websites in our sample are from diverse industries (Figure W 1 in Web Appendix A), audiences, and sizes (measured by SimilarWeb ranks). For each website in our sample, the dataset includes information about the website's industry and size, measured by its global, country, and industry rank.⁴

For each website in the sample, the dataset includes information on the usage metrics of users accessing that website from the EU country where the website has the largest following. Additionally, usage metrics are available for users accessing each website from the United States. Thus, data are available only for US users if a website does not appear in the top 1,000 of any EU country. These data span between July 1st, 2017, and December 31st, 2019—almost a year before and 18 months after the GDPR's enactment—allowing for a before-and-after analysis as outlined above.

Discussion of measurement error due to non-consenting users. One potential concern regarding our data is that GDPR may lead to a measurement error, as the recorded usage behavior by SimilarWeb may not correspond to the actual usage behavior post-GDPR if not all users consent to be tracked. As a result, the recorded usage behavior post-GDPR may be a function of the share of consenting users and the actual usage behavior.

³ During our study, the UK was still a member of the EU. Its membership ended on January 31th, 2020.

⁴ SimilarWeb's rank measures a website's size based on estimations of a site's monthly unique visitors and monthly page impressions. The higher the two values, the better the site's rank.

We address the suitability of SimilarWeb data in Web Appendix F, where we compare SimilarWeb data empirically with ground-truth data provided by another data provider, AGOF. We conclude that the measurement error in SimilarWeb data due to non-consenting users should be minimal, as we do not find a statistical difference in GDPR's estimated effect based on SimilarWeb and AGOF data. AGOF data represents a complete technical measurement of online usage behavior and are collected without relying on user consent, thus not suffering from measurement error due to the GDPR itself. SimilarWeb removes all personally identifiable information at the source, keeping SimilarWeb outside the GDPR jurisdiction. Indeed, the GDPR only applies to processing personal data, not non-personal data, which SimilarWeb generates. This type of data differs from the tracking data used for targeted advertising. Overall, SimilarWeb data should serve our purpose of measuring GDPR's effect on online usage behavior.

Description of sample construction. We start with data on the top 1,000 websites for each of the 13 countries focused on in our study (Table 2). After removing duplicate websites, our sample includes 7,332 unique websites (Step 1 in Table 2). For example, "google.com" is a duplicate website because it is among the top 1,000 websites in all 13 countries. Instead of occurring 13 times, google.com occurs only once in our sample. We have data for non-EU users for each of these 7,332 websites and data for EU users for 6,460 of them.

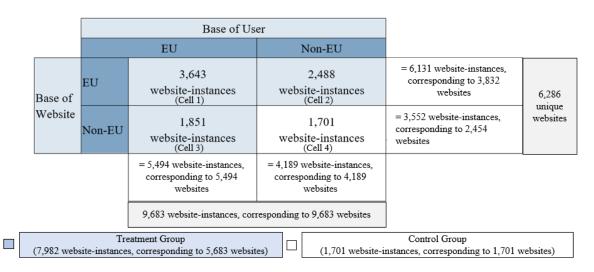
Thus, for 6,460 websites, we have two sets of observations corresponding to non-EU and EU users of each website. For the remaining 872 websites, we observe only non-EU users. In what follows, we consider each website's non-EU and EU users separately and refer to each combination of a website with one of the two user groups (EU or non-EU) as a "website-instance." For example, for a website such as "zeit.de," which is based in an EU country (Germany), we observe two website-instances: one corresponding to the EU users of "zeit.de" and the other corresponding to the non-EU users of "zeit.de." As "zeit.de" is EU-based, the GDPR applies to both website-instances. Thus, both belong to the treatment group (Figure 1).

Website-Instances with EU users	Website-Instances with non-EU users	Website-Instances Total
13,000	13,000	26,000
6,460	7,332	13,792
6,302	5,071	11,373
5,494	4,189	9,683
5,105	3,103	8,208
-	with EU users 13,000 6,460 6,302 5,494	with EU users with non-EU users 13,000 13,000 6,460 7,332 6,302 5,071 5,494 4,189

Table 2: Derivation of Final Sample of Website-Instances

Note: SimilarWeb does not report unique visitor information for websites with < 5,000 unique visitors per month. Thus, the final sample for the unique visitor analysis contains only website-instances with $\geq 5,000$ unique visitors per month throughout the entire observation period.

Table 3: Distribution of Website-Instances According to Bases of Users and Websites



Reading Example: Table 3 illustrates the number of website-instances across the treatment and control groups. For example, Cell 1 in the first row shows that 3,643 website-instances belong to a website with an EU base that EU users visit. Cell 2 in the first-row outlines that 2,488 website-instances (Cell 2) belong to a website with an EU base that Non-EU users visit. Some websites have EU and Non-EU users; others do not. So, the number of websites that belong to these website-instances is more than half but less than the sum. In our setting, the 6,131 website-instances in the first row (Cell 1 + Cell 2) correspond to 3,832 websites.

The website-instances in the columns distinguish between websites in the EU and Non-EU, i.e., outside of the EU. They refer to the same website. So, the sum of website-instances in a column equals the number of websites.

Similarly, for a non-EU website such as "nzz.ch" (Switzerland), we observe two website-

instances: one corresponding to the non-EU users of "nzz.ch" and the other corresponding to the

EU users. The GDPR applies only to the website-instance with EU users of "nzz.ch," which

belongs to the treatment group, but not to the non-EU users, which belong to the control group (Figure 1).

Overall, the sample includes 7,332 website-instances corresponding to observations of non-EU users and 6,460 website-instances corresponding to observations of EU users, totaling 13,792 website-instances. We then drop website-instances for which the users generated, on average, fewer than 1,000 weekly visits (Step 2). We drop website-instances with zero visits in at least one month⁵, and avoid errors in the data by dropping website-instances that exhibited significant unexplained changes in traffic (Step 3).

This procedure results in a final sample of 9,683 website-instances belonging to 6,286 unique websites (Table 3). For 3,397 of these websites, we have two website-instances (EU and non-EU users), and for the remaining 2,889 websites, we have one website-instance (EU or non-EU users), totaling 9,683 website-instances (= $2 \times 3,397 + 2,889$).

SimilarWeb does not report unique visitor information for websites with fewer than 5,000 unique visitors per month. Therefore, the unique visitor analysis contains a smaller set of 5,198 treatment websites.

Table 3 outlines how the 9,683 website-instances split into the four cells. Cells 1-3 belong to the treatment group and contain 7,982 (= 3,643 + 2,488 + 1,851) website-instances. They belong to 5,683 (= 3,832 + 1,851) websites, encompassing over 1.15 trillion website visits from the EU during our observation period. Our control group consists of 1,701 (= 9,683 - 7,982) website-instances, corresponding to the same number of websites (Table 3), encompassing almost 1.8 trillion website visits from Switzerland and the United States during our observation period.

Description of variables. Table 4 defines our variables of interest as online usage, user quantity and usage intensity metrics. Our main online usage metric to gauge the impact of the GDPR is weekly visits. To understand the mechanism behind GDPR's effect on visits, we decompose visits

⁵ We test the sensitivity of only selecting websites with more than 1,000 average weekly visits in Web Appendix C and discuss the result in greater detail below when assessing the heterogeneity of the effect of GDPR.

into a user quantity metric—monthly unique visitors—and a usage intensity metric—visits per unique visitor. In our robustness tests, we also study the impact of the GDPR on weekly page impressions and decompose it into weekly visits and page impressions per visit.

We analyze all usage behavior and user quantity metrics weekly, except unique visitors, for which data are available only monthly. Due to large differences in the values of each metric across websites and countries, we convert all usage behavior and user quantity metrics (adding 1 to avoid zero values) to their natural logarithm to capture relative (i.e., percentage) effects. Figure 2 shows pre- and post-GDPR trends of our main variable, weekly visits.

We initially calculate GDPR's effect on the usage behavior and user quantity metrics per website-instance. We then determine GDPR's effect per website. For 2,683 EU websites (= 70% of the 3,832 EU websites; Table 3)⁶, we have two (treatment) website-instances: one for EU and one for non-EU users. For these websites, the GDPR's overall effect incorporates the effects of both website-instances. When merging the two effects, we consider the relative sizes of the two websiteinstances pre-GDPR. For example, the website "zeit.de," a reputable German online news website, received 98.94% of its visits from German (EU) users. Thus, GDPR's effect on visits to the website "zeit.de" comprises 98.94% of its effect on the website-instance corresponding to the EU users and 1.06% on the website-instance corresponding to the non-EU users. This weighting procedure results in the same GDPR effect as combining the two website-instances from the beginning of the calculation.

Description of Methodology to Analyze Data

We do not observe a control group for some website-instances, such as those where the GDPR affected both website-instances of a website. Thus, we examine GDPR's effect on the various usage behavior metrics using a GSC estimator (Xu 2017) and exploit the GDPR as the "treatment"

⁶ For the remaining 1,149 EU websites (= 30% of the 3,832 EU websites) and all 2,454 non-EU websites, GDPR's effect on that website comprises only the effect of one website-instance.

event. The GSC is similar in spirit to a DID approach and enables us to examine the effect of the

GDPR on usage behavior compared to our synthetic control group.

Online Usage Metric	User Quantity Metric	Usage Intensity Metric	Corresponding Formula
Weekly Visits	Monthly Unique Visitors	Visits per Unique Visitor	
Number of visits to a website in a week Measure of website's traffic volume	Number of unique users visiting a website in a month Measure of website's reach	Average number of visits per unique visitor	Visits = Unique Visitors <u>Visits</u> Unique Visitors
Weekly Page Impressions	Weekly Visits	Page Impressions per Visit	
Number of pages visited on a website in a week by the entire user base Measure of website's ability to spark engagement	Number of visits to a website in a week Measure of website's traffic volume	Average number of pages viewed per visit	Page Impressions = Visits Page Impressions Visits

 Table 4:
 Relationship between Online Usage, User Quantity and Usage Intensity Metrics

Description of methodology to analyze usage behavior and user quantity metrics. Following Xu (2017), we estimate the following regression model using the GSC to determine GDPR's effect on online usage behavior:

(1)
$$ln(Y_{q,t,wi} + 1) = \delta_{q,wi} * Treated_{t,wi} + \lambda'_{wi} * f_t + \epsilon_{q,t,wi}$$

where q indexes the usage behavior or user quantity metric Y for website-instance wi in week t (when the dependent variable is unique visitors, the scale of t is one month). *Treated*_{t,wi} is a binary indicator variable for which a value of 1 indicates that in week t, website-instance wi needs to consider GDPR; otherwise, it is 0. The term $\delta_{q,wi}$ is the coefficient of interest and captures GDPR's effect for user quantity metric q on website-instance wi. The term $f_t =$ $[f_{1,t}, f_{2,t}, ..., f_{r,t}]$ is a vector of r unobserved common factors in week t for website-instance wi while $\lambda'_{wi} = [\lambda_{1,wi}, \lambda_{2,wi}, ..., \lambda_{r,wi}]$ denotes the corresponding factor loadings for website-instance wi. Although the same set of factors influences the treated and control groups, each websiteinstance can have different factor loadings. Note that cross-sectional controls in the form of website-instance fixed effects and time (week or month) fixed effects can be considered two special cases of the unobserved factors by setting $f_t = 1$ and $\lambda'_{wi} = 1$. In all our model specifications, we impose additive two-way fixed effects— a stringent nonparametric way of accounting for the possibly evolving nature of unobservables specific to treated and control units (Xu 2017, p. 60). Website-instance fixed effects absorb all cross-sectional differences that are constant over time. Time fixed effects absorb common intertemporal changes across all website-instances. $\epsilon_{q,t,wi}$ represents an unobserved idiosyncratic shock for user quantity metric q in week t for website-instance wi. We use the regression model Equation (1) and the control and treatment group assignment described in Figure 1 to calculate the treatment effect $\delta_{q,wi}$ for every website-instance wi for each user quantity metric q.

To determine the development of the treatment effect over time, we rerun our analysis multiple times, extending the duration of the post-GDPR observation period in each analysis. We first consider a post-treatment period of 3 months post-GDPR (up to August 25th, 2018, thus including observations from week 1 to 60), then periods of 6 (week 1 to 73), 9 (week 1 to 86), 12 (week 1 to 99) and 18 (week 1 to 125) months. These analyses enable us to determine GDPR's short-term (3 months post-GDPR) and long-term (up to 18 months post-GDPR) effects.

We rely on the GSC estimator (Xu 2017), which entails a synthetic construction of a control group whose pre-treatment changes in the dependent variable over time are comparable to those of the treatment group. The estimator constructs this matched control group by selecting, for each treatment website-instance, a weighted combination of several control website-instances. This approach reduces reliance on the parallel pre-treatment trends on which DID estimators are predicated (Abadie et al. 2010, Xu 2017). The estimator then calculates the post-treatment metric of interest for the synthetic control website-instance that serves as the treatment website-instance's counterfactual.

For each metric, we follow Abadie (2021) and Abadie et al. (2014) and carefully choose the set of control website-instances (referred to as the "donor pool") to obtain a reasonable synthetic control for the treatment website-instance. The donor pool should avoid (i) the risk of overfitting, which would occur if it is too large, and (ii) the risk of bias, occurring when there are large differences in observed or unobserved factors compared to the treatment website-instance.

Therefore, we select (i) five website-instances that (ii) belong to the same industry as the treatment website-instance and (iii) have the highest pre-treatment correlations with the respective metric of the treatment website-instance.

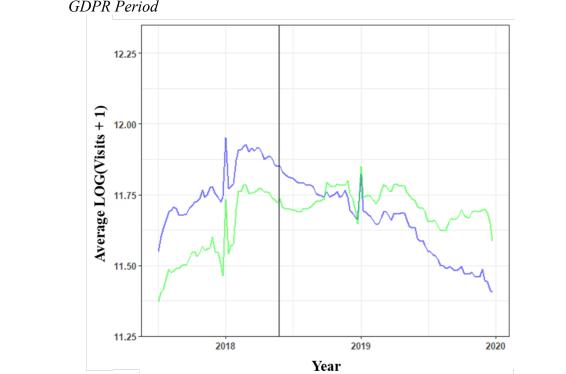


Figure 2: Average LOG(Visits + 1) between Treatment and Control Group and Pre- and Post-GDPR Period

Notes: Blue Line = Treatment Group Average log(Visits + 1). Treatment Group includes EU website-instances with EU user traffic (Cell 1 in Figure 1), EU website-instances with Non-EU user traffic (Cell 2), and Non-EU website-instances with EU user traffic (Cell 3). Green Line = Control Group Average log(Visits + 1). Control Group includes Non-EU website-instances with Non-EU user traffic (Cell 4). Black Vertical Line = Enactment date of GDPR (May 25th, 2018).

Using these five control website-instances as a donor pool, we follow the approach outlined above and use the GSC estimator to calculate the weights of these website-instances to create a synthetic control website-instance that exhibits a similar pre-treatment pattern as the treatment website-instance. The estimator uses the weights and observed values of the five website-instances to calculate a synthetic time series for the synthetic control website-instance, spanning the post-treatment period. The outcomes of these calculations serve as the control group to determine the effect of the treatment on the metric of interest for all website-instances. We repeat the process for each user quantity metric q and website-instance wi.

We then determine GDPR's effect on a website, referred to as Δ , as described above. If a website has only one website-instance, GDPR's effect on that website-instance and online usage or user quantity metric ($\delta_{q,wi}$, as calculated in Equation (1)) determines GDPR's effect on that website (Δ). If a website has two website-instances, GDPR's weighted effects on both website-instances for the online usage or user quantity metric (two treatment effects $\delta_{q,wi}$) determine GDPR's effect on that website that website (Δ), using the relative average sizes of the two website-instances in the entire pretreatment period as weights.

Description of methodology to analyze usage intensity metrics. After these steps, we use these treatment effects for all websites and post-treatment periods to examine the change in our usage intensity metrics for each website over time. For this examination, we take advantage of two aspects: First, each usage intensity metric is a function of two user quantity metrics. For example, the visits per unique visitor are a function of the visits and the unique visitors:

(2) Visits per Unique Visitor_w =
$$\frac{Visits_w}{Unique Visitor_w}$$

Second, the treatment effects calculated with Equation (1) represent relative (i.e., approximately percentage) changes of our user quantity metrics for each post-treatment period p. Thus, to determine the relative change of visits per unique visitor for a particular website w for a particular post-treatment period p, we include GDPR's effect Δ in Equation (2):

(3) Visits per Unique Visitor_w * $(1 + \Delta Visits per Unique Visitor_{p,w}) = \frac{Visits_w * (1 + \Delta Visits_{p,w})}{Unique Visitors_w * (1 + \Delta Unique Visitor_{p,w})}$

We use Equation (1) to calculate GDPR's effect, reflected in Δ , for the two user quantity metrics (unique visitors and visits). To determine the effect on the usage intensity metric (visits per unique visitor), we rearrange Equation (3):

(4)
$$\Delta$$
 Visits per Unique Visitor_{p,w} = $\frac{1 + \Delta Visits_{p,w}}{1 + \Delta Unique Visitor_{p,w}} - 1$

Δ Visits per Unique Visitor _{p,w} :	GDPR's effect in period p on visits per unique visitor for website w
Δ Visits _{p,w} :	GDPR's effect in period p on visits for website w
Δ Unique Visitors _{p,w} :	GDPR's effect in period p on unique visitors for website w

This process (see Web Appendix B for a derivation of Equations (3) and (4)) enables us to determine GDPR's effect on visits per unique visitor for each website and each post-treatment period p (i.e., after 3, 6, 9, 12, and 18 months of GDPR). We calculate GDPR's effect on page impressions per visit by applying the same procedure:

(5) Δ Page Impressions per Visit_{p,w} = $\frac{1 + \Delta Page Impressions c_{p,q,w}}{1 + \Delta Visits_{p,w}} - 1$

 Δ Page Impression per Visit_{p,w}: Δ Page Impressions _{p,q,w}: Δ Visits_{p,w}: GDPR's effect on page impressions per visit in period p for website wGDPR's effect on page impressions in period p for website wGDPR's effect on visits in period p for website w

RESULTS OF EMPIRICAL STUDY

GDPR's Effect on Online Usage

We begin our analysis by assessing the effect of the GDPR on online usage, specifically focusing on weekly visits and page impressions as metrics.

In the 3 months following GDPR's enactment, treatment websites experience a decline in mean weekly visits of 4.88% (see Table 5). Over time, this decrease became even more substantial: by 18 months post-GDPR, mean weekly visits to treatment websites were 10.02% lower. Figure 3 visualizes the strengthening of GDPR's effect on weekly visits over time.

We also separately assess the negative and positive effects of the GDPR on weekly visits. Many websites experience a statistically significant negative effect from GDPR (p < .05). 3 months post-GDPR, about one-third of the websites (32.20%) experienced a significant negative effect (the red line in Figure 4 plots the share of significantly negatively affected websites). The share of significantly negatively affected websites rose to 54.87% 18 months post-GDPR.

Metric		Post-Treatment Period					
		3 months	6 months	9 months	12 months	18 months	
Visits	Mean:	-4.88%	-7.22%	-9.07%	-9.57%	-10.02%	
	Median:	-3.49%	-5.54%	-7.54%	-8.24%	-8.91%	
	Share of statistically significant positive effects:	17.74%	19.97%	20.16%	20.80%	23.96%	
	Share of statistically significant negative effects:	32.20%	42.81%	50.48%	53.25%	54.87%	
Page	Mean:	-3.12%	-4.83%	-6.33%	-6.48%	-9.28%	
Impressions	Median:	-2.75%	-3.92%	-5.44%	-6.04%	-9.29%	
	Share of statistically significant positive effects:	18.79%	22.73%	23.98%	25.61%	24.64%	
	Share of statistically significant negative effects:	27.74%	35.83%	42.23%	44.90%	51.44%	

 Table 5:
 Summary of the Effect of GDPR on Online Usage Metrics

Notes: The table summarizes the effect of GDPR on online usage metrics. The table shows the mean and median values of the change in the metrics due to GDPR across all websites, the share of websites with a statistically significant positive GDPR effect and the share of statistically significant negative GDPR effect (on the 5%-level) of all websites for each period.

Reading example: On average, the 3-month effect of GDPR for the weekly visits (second-row / third column) was -4.88% per website. The median effect is -3.49% per website. 17.74% (32.20%) of all websites are statistically positively (negatively) affected.

Conversely, 3 months post-GDPR, 17.74% of all websites were positively affected by the GDPR (the blue line in Figure 4 plots the share of positively affected websites). The share of websites experiencing an increase in visits rose to 23.96% after 18 months.

Interestingly, about 50% of the websites were unaffected by the GDPR 3 months post-enactment, but only 21% remained unaffected after 18 months. This finding suggests that privacy laws like the GDPR take some time to become fully effective, and a longer observation window is necessary to capture their impact on EU websites.

The results for page impressions are comparable to our main online usage metric, weekly visits, despite small differences in the effect size (see Web Appendix A for further details)⁷. The GDPR negatively affected page impressions in all examined periods, and we observe that the negative effect strengthens over time.

⁷ For robustness, we assessed the impact of the GDPR on other usage behavior metrics such as time on website and bouncing visitors and obtained similar results. For concideness, we do not report the details of this analysis here.

Figure 3: Distribution of the Effect of GDPR on Weekly Visits over Time

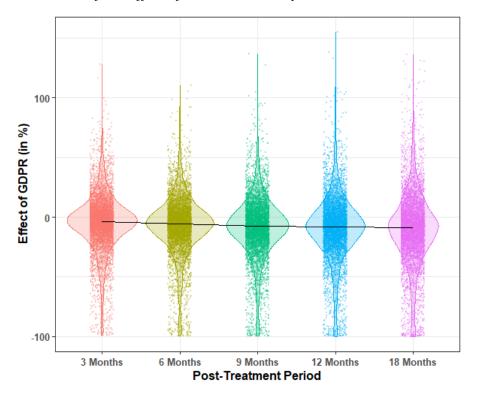
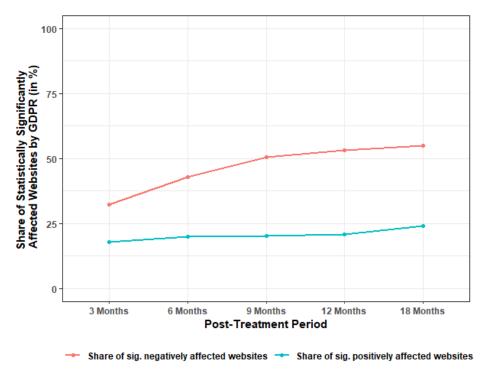


Figure 4: Share of Websites with a Statistically Significant Positive or Negative Effect of GDPR on Weekly Visits over Time



Notes: The share of significantly negatively affected websites is the number of websites statistically significantly negatively affected by GDPR (p < .05) relative to all websites. The share of significantly positively affected websites depicts the statistically significantly positively affected websites by GDPR (p < .05) relative to all websites.

Our findings resonate with those of Goldberg et al. (2024), who observed a significant

reduction in page views post-GDPR. Goldberg et al. employed a selection model with multiple

assumptions to account for non-consenting users, estimating GDPR's effect on page views to be within the range of 0.00% to 8.10%, and on e-commerce revenue between 0.00% and 13.20% four months after its implementation. These findings closely align with our own, which show a 3.12% decrease in page impressions (with a 95% confidence interval of 2.37% to 3.87%) 3 months post-GDPR and a 4.83% decrease (confidence interval of 4.08% to 5.58%) after six months.

Moreover, our results are consistent with those of Wang et al. (2024), who also account for nonconsenting users and found a decrease of 5.4% in conversion rates, a 5.6% drop in ad bid prices, and a 5.7% reduction in revenue per click for advertisers, observed five weeks after GDPR implementation.

The observed decreases post-GDPR could be attributed to user privacy preferences and reduced marketing effectiveness. Budak et al. (2016) provide a conservative estimate that approximately 23% of site traffic is driven solely by various forms of digital advertising, such as search ads (8%), email (7%), display ads (3%), and social ads (3%). Their finding underscores the potential for diminished marketing effectiveness as a plausible explanation for the reduced user engagement observed post-GDPR.

Decomposition of GDPR's Effect on Online Usage Metrics

To better understand the mechanism behind GDPR's effect, we decompose its impact on online usage into a user quantity and a usage intensity metric. Specifically, we decompose the effect of GDPR on visits into the effect on unique visitors and visits per unique visitor. This analysis focuses on GDPR's effect after 3 and 18 months (see Table 6).

3 months post-GDPR, weekly visits decreased by 4.88% and by 10.02% after 18 months. Visits are the product of unique visitors and average visits per visitor. Thus, two factors could drive the decrease in visits:

- Unique Visitors: Unique visitors decreased by 0.77% three months post-GDPR and by 6.61% after 18 months. Such a drop in unique visitors is consistent with users abandoning certain websites post-GDPR to prevent sharing their data.
- Visits per Unique Visitor: The remaining unique visitors also returned less frequently, as indicated by a 1.62% decrease in the average visits per unique visitor 3 months post-GDPR. At 18 months post-GDPR, the average visits per unique visitor reduced less (-0.59%).

To assess the negative and positive effects of privacy regulation, we further examine GDPR's effect on the usage intensity metric of visits per unique visitor by dividing the websites into two groups based on whether they experienced an increase or a decrease in unique visitors. Specifically, unique visitors increase by 46.60% and 38.27% after 3 and 18 months of the GDPR.

Using this classification, we observe that the direction of GDPR's average effect on visits per unique visitor aligns for the two groups:

- 1. Websites with Increased Unique Visitors: These websites exhibited an average decrease in visits per unique visitor.
- Websites with Decreased Unique Visitors: These websites showed an average increase in visits per unique visitor.

The corresponding effects on usage intensity become even stronger over time; that is, the positive effects increase, and the negative effects decrease (become more negative). For example, 3 months post-GDPR, websites that gained unique visitors experienced a 6.46% average decrease in visits per unique visitor; after 18 months, average visits per unique visitor decreased by 9.09%. Conversely, websites that lost unique visitors experienced a 2.56% increase in average visits per unique visitor after 3 months and 4.77% after 18 months post-GDPR.

To examine the robustness of our results, we also decompose the effect of the GDPR on page impressions into its effects on visits and page impressions per visit. 3 months post-GDPR, page impressions decreased by 3.12% and by 9.28% after 18 months. Page impressions are the product of visits and the average page impressions per visit. Thus, the decrease in page impressions can have two reasons:

- Visits: As outlined above, weekly visits decreased by 4.88% 3 months post-GDPR and by 10.02% after 18 months.
- 2. **Page Impressions per Visit:** When visiting a website, the average page impressions per visit increased from 1.97% (3 months post-GDPR) to 2.15% (18 months post-GDPR).

As with visits per unique visitor, we further examine page impressions per visit by forming two groups of websites: those with an increase and those with a decrease in visits after GDPR. Specifically, visits increased for 40.69% of websites 3 months post-GDPR and 33.30% after 18 months.

We observe the same effect directions as for visits per unique visitor:

- 1. Websites with Increased Visits: Average page impressions per visit decreased by 2.44% (3 months post-GDPR) and by 4.58% (18 months post-GDPR).
- Websites with Decreased Visits: Average page impressions per visit increased by 5.05% (3 months post-GDPR) and by 5.53% (18 months post-GDPR).

Thus, GDPR's effect on usage intensity metrics partly counteracts its effect on user quantity, as an increase in user quantity is associated with a decrease in usage intensity and vice versa. For example, among websites that lost unique visitors post-GDPR, the remaining visitors used the website more intensively than pre-GDPR: The average user makes more visits to those websites (e.g., 4.77% more visits per unique visitor 18 months post-GDPR) and engaged more during each visit, as reflected in increases in the page impressions per visit (5.53%). Websites that gain unique visitors experience the opposite effect.

Our results for the usage intensity metrics show that the websites gaining (losing) unique visitors and visits experience an increasingly negative (positive) GDPR effect on usage intensity over time. Together, these results suggest that, on average, the GDPR negatively affects websites in

two major ways: either the website experiences difficulties in attracting users or, having attracted users, it struggles to keep them engaged and loyal.

These results align with previous studies showing that the GDPR affected different websites differently. For some websites, users exhibited positive responses due to the website's adjustments to the GDPR, potentially due to lower privacy concerns (e.g., Martin 2015) or higher trust in the website (e.g., Martin et al. 2017). Users may have reacted negatively to other websites, potentially due to increased awareness of data disclosure activities or heightened privacy concerns (e.g., Dinev and Hart 2006). The steady growth in websites' use of consent management tools post-GDPR may partly trigger such an increase in privacy concerns (Hils et al. 2020). However, the users did not change their behavior for other websites, potentially due to actual behavior not reflecting the stated privacy preferences (e.g., Acquisti 2004) or a continued feeling of powerlessness (Few 2018) even after the GDPR.

Interestingly, Lefrere et al. (2024) found an average decrease in the number of pages browsed daily by about 0.09 pages per user six months post-GDPR but did not find an effect on content provision. In contrast, Goldberg et al. (2024) found increased usage intensity, as measured by the recorded page views per visit (4.50% four months post-GDPR). We also find a slightly lower increase in page impressions per visit of 1.97% 3 months post-GDPR and 2.15% 18 months post-GDPR.

Assuming no overall increase in internet usage post-GDPR, our results on usage intensity are consistent with a reallocation of user engagement toward websites they value and trust. Consistent with the sunk-cost effect (Arkes and Blumer 1985), users may prefer websites to which they have already provided data and thus use them more.

Impact of Website and User Characteristics on the Effect of GDPR

The previous section demonstrated that the GDPR's impact on online usage, user quantity and usage intensity varied across websites, indicating differential effects. In this section, we analyze how GDPR's effect on online usage differs based on website characteristics—specifically, website industry and website size—and a user characteristic, namely, the user's country of origin. For each analysis, we categorize websites according to the focal feature (e.g., website industry) and calculate the GDPR's average effect on our main online usage metric, weekly visits, across all websites within each category.

Impact of the industry of the websites on the effect of GDPR. Our analysis reveals that the GDPR affected industries differently (see Table W 1 in Web Appendix A). Websites within the "Heavy Industry and Engineering" and "Gambling" sectors experienced the most significant negative effects, losing, on average, 46.41% and 19.17% of their visits 3 months post-GDPR, respectively. Other industries that faced substantial declines include "Lifestyle" (-9.04%), "Games" (-8.43%), "Arts and Entertainment" (-8.03%), "Reference Materials" (-7.74%), and "Hobbies and Leisure" (-7.33%). Conversely, websites in the "Vehicles" industry experienced positive effects, with increases ranging from 1.80% to 5.26% in visits.

Interestingly, some industries exhibited positive effects 3 months post-GDPR but transitioned to negative effects after 18 months. For instance, "Business and Consumer Services" shifted from a 4.31% increase to a 1.57% decrease, "Travel and Tourism" from a 3.13% increase to a 2.10% decrease, and "E-Commerce and Shopping" from a 0.14% increase to a 3.37% decrease.

These variations may reflect differences in users' privacy expectations across industries. Users visiting entertainment websites might have been less aware of data collection practices than those on e-commerce websites, where providing personal information is necessary for transactions. Consequently, increased transparency about data collection could have been more surprising to users of entertainment websites, leading to more substantial behavioral changes. In contrast, users seeking services may perceive the benefits of continuing to use a website as outweighing any potential disadvantages, and they may even appreciate the added privacy safeguards.

Impact of website size on the effect of GDPR. To examine how website size influences the heterogeneity of GDPR's effect, we conducted two analyses: First, we divided the websites into

deciles based on their global, country, and industry ranks. Second, we reanalyzed our data without the threshold of an average of 1,000 weekly visits to assess the impact on low-traffic websites (Web Appendix C).

In the first analysis, we group websites into deciles, with the top 10% (lowest rank numbers) forming the first decile and the bottom 10% forming the tenth decile. Table W 2 in Web Appendix A presents the GDPR's average effect on weekly visits per industry rank decile. Analyses based on the global and country ranks yielded similar results.

Our findings indicate that website size, measured by monthly unique visitors and page impressions, significantly influences the GDPR's impact. Consistent with Campbell et al. (2015), who showed that privacy laws particularly harm smaller firms, we found that smaller websites suffered more negative effects than larger ones. Specifically, websites in the bottom decile experienced the most significant declines, with a 13.89\$ drop in visits 3 months post-GDPR, escalating to a 21.49% drop after 18 months. Websites in the 6th to 9th deciles exhibited a decrease in visits ranging from 4.30% to 6.23% after thee months and from 10.31% to 11.51% after 18 months.

This trend suggests that users reacted less negatively to the GDPR-induced changes on larger websites than on smaller ones, indicating increased market concentration post-GDPR. This result aligns with prior findings that the GDPR led to greater market concentration in page views and revenue (Goldberg et al. 2024) and in web technology services (Johnson et al. 2023, Peukert et al. 2022). The GDPR also discouraged investment in newer technology firms (Jia et al., 2021).

These effects may reflect users' stronger motivation to continue using larger, more valued websites despite potential disadvantages created by the GDPR, such as increased awareness of data disclosure or diminished convenience due to compliance measures. Larger sites may have benefited from the GDPR as they more readily obtained consent (Campbell et al. 2015) or relied less on push marketing. In contrast, users may have perceived that the benefits of using smaller websites did not outweigh the disadvantages, leading them to discontinue use.

Metric		3 months			18 months			
			Share of Websites	Median Effect	Mean Effect	Share of Websites	Median Effect	Mean Effect
Online Usage	Visits		-	-3.49%	-4.88%	-	-8.91%	-10.02%
User Quantity	Unique Visitors		-	-1.24%	-0.77%	-	-6.65%	-6.61%
Usage Intensity	Visits per Unique Visitor	All Treatment Websites	100.00%	-2.62%	-1.62%	100.00%	-2.81%	-0.59%
		Treatment Websites that Gain Unique Visitors	46.60%	-6.19%	-6.46%	38.27%	-9.37%	-9.09%
		Treatment Websites that Lose Unique Visitors	53.40%	+1.23%	+2.56%	61.73%	+1.39%	+4.77%
Online Usage	Page Impressions		-	-2.75%	-3.12%	-	-9.29%	-9.28%
User Quantity	Visits		-	-3.49%	-4.88%	-	-8.91%	-10.02%
Usage Intensity	Page Impressions per Visit	All Treatment Websites	100.00%	+0.56%	+1.97%	100.00%	+0.28%	+2.15%
		Treatment Websites that Gain Visits	40.69%	-2.92%	-2.44%	33.30%	-4.87%	-4.58%
		Treatment Websites that Lose Visits	59.31%	+3.07%	+5.05%	66.70%	+3.11%	+5.53%

Table 6:Summary of the Decomposition of the Effect of GDPR on Online Usage in User
Quantity and Usage Intensity Metrics

The table summarizes the decomposition of the effect of the GDPR on online usage in a user quantity and a usage intensity metric. The table shows the mean and median values of the change in the online usage metrics, the user quantity metrics and the usage intensity metrics due to GDPR. The table shows the usage intensity metrics for 1) all websites, 2) the websites that experience positive user quantity effects, and 3) the websites that experience negative user quantity effects in each analyzed period. For example, the average 3-month effect of GDPR for visits is -4.88% (third row/ fifth column), the average effect on unique visitors is -0.77% (fourth row / fifth column), and the average effect of visits per unique visitor over all websites (fifth row / fifth column) is - 1.62%.

In our second analysis, we reexamined our data without the threshold of an average of 1,000 weekly visits (see Web Appendix C). We found that including low-traffic websites did not lead to an overestimation of GDPR's effect. Instead, the unconstrained sample exhibited more negative effects than the more trafficked websites in our main analysis. This finding reinforces the conclusion that low-traffic websites were more adversely affected, further supporting the notion of increased market concentration post-GDPR.

Impact of a user's country of origin on the effect of GDPR. To explore the relationship between a user's country of origin and GDPR's effect, we categorized each website according to the country with the largest user base. Our dataset provides user data for US users and the country where the

website is largest. Table W 3 in Web Appendix A indicates that GDPR's effect varied by the user's country of origin, reflecting cultural differences across countries.

Websites whose primary users come from Denmark, Poland, or Germany suffered the least from GDPR over the analyzed period. Visits from users based in these countries decreased, on average, by 1.06% (Denmark), 2.27% (Poland), and 2.87% (Germany) 3 months post-GDPR, and by 6.97%, 5.55%, and 6.55%, respectively, after 18 months. In contrast, the most substantial drops in website visits occurred for users from Austria (-8.45% after 3 months, -9.21% after 18 months), Sweden (-7.90%, -13.36%), the UK (-7.47%, -12.57%), the Netherlands (-7.28%, -17.20%), Hungary (-7.28%, -11.80%), and Switzerland (-5.55%, -12.20%).

ROBUSTNESS OF RESULTS OF EMPIRICAL STUDY

Identifying Assumptions of the Generalized Synthetic Control Estimator

The validity of the GSC estimator relies on several key assumptions. Table 7 summarizes our identification assumptions, challenges, solutions, implementations, and whether additional tests support the robustness of our main results.

Composition of the Donor Pool: The first assumption is that the donor pool must yield a good synthetic control group (Abadie et al. 2010; Abadie 2021). We accomplished this aim by selecting (i) five website-instances that (ii) belong to the same industry as the treatment website-instance and (iii) have the highest pre-treatment correlations with the respective metric of the treatment website-instance. To test the robustness of our results, we conducted additional analyses detailed in Web Appendix H. Specifically, we recalculated GDPR's effect (i) without requiring the control websites to be in the same industry as the treatment website, (ii) requiring the control website-instances to be part of a website with a treated website-instance with a similar share of EU traffic as the focal treatment website-instance, and (iii) using ten instead of five control websites. Web Appendix H shows no significant difference in GDPR's effect across our main and alternative specifications of the donor pool, indicating that our results are robust to these specifications.

Identification Assumption	Challenge	Solution	Implementation	Supports Robustness of Results
Composition of the Donor Pool	Identify control websites with similar characteristics as treatment websites	Select as control group five website-instances (10 in robustness test) that belong to the same industry (no industry restriction or similar EU traffic share instead of the same industry for robustness) and have a high pre-treatment correlation.	Main Specification GSC, Robustness Check GSC (Web Appendix H)	
No Anticipation of Treatment	Early- or Late- GDPR compliance of treatment websites	Window analysis, which removes 30 days before & post-GDPR's enactment	Robustness Check GSC (Web Appendix D)	\checkmark
No Interference (SUTVA)	Voluntary GDPR compliance of control websites	Analysis of control websites based on share of EU traffic	Robustness Check GSC (Web Appendix E) (Web Appendix H)	a V
		Analysis of EU websites and non-EU websites for non-EU users	Robustness Check GSC (Web Appendix E)	
		Analysis of EU users and non-EU users for non-EU websites	Robustness Check GSC (Web Appendix E)	a V
			Robustness Check DID (Web Appendix I)	
		Analysis of non-EU user interface on control websites	Robustness Check (Web Appendix E)	a V
	Self-selection of EU websites to control group (non-compliance of treatment websites)	Analysis of strategic geographic shifts of website server locations	Robustness Check GSC (Web Appendix E)	
Unconfoundedness	Coincidence of GDPR's enactment with other major changes in confounding factors	Analysis of differences in internet speed, share of population with internet access, laptop, and smartphone across EU and non-EU users	Robustness Check (Web Appendix G)	\checkmark

Table 7: Identification Assumptions, Challenges, Solutions, Implementations, and Results

No Anticipation of Treatment: The second assumption is that the treatment coincides with the enactment of the GDPR (May 25th, 2018) to enable a valid before-and-after analysis comparing the treatment and control groups. Although Perunicic (2018) notes that very few websites were compliant before enactment, we examine whether websites were either early or late in being

GDPR-compliant, as this could affect the validity of our results if the treatment's timing differed from GDPR's enactment date.

In Web Appendix D, we replicate our analysis while removing observations from 30 days before and after the GDPR's enactment. We then calculate the GDPR's short-term (i.e., three months post-enactment) and long-term (i.e., 18 months post-enactment) effects on our main online usage behavior metric, weekly visits for all websites. We observe no significant differences in GDPR's effect across websites for either the short- or long-term periods (see Table W 6). This finding suggests that early or late compliance does not bias our results.

No Interference (Stable Unit Treatment Value Assumption): The third assumption is that only treatment website-instances receive the treatment, not the website-instances contributing to the synthetic control group. Our control group consists of website-instances of non-EU websites and non-EU users (Cell 4 in Figure 1). However, non-EU websites could voluntarily comply with the GDPR for non-EU users, resulting in a potential spillover effect of GDPR to our control group. Such a spillover effect would reduce the suitability of our control group as some control websites would effectively be treated. Therefore, we further examine our control group through several analyses:

1. Analysis Based on EU User Share: We examine non-EU websites based on their incentive to comply with GDPR. Non-Eu websites with a higher share of EU users may be more incentivized to comply voluntarily. We divide non-EU websites into two groups in Web Appendix E based on their EU user share. 3 months post-GDPR, we find a significantly stronger GDPR effect for the group of websites with a low EU user share. This finding is consistent with our conjecture that non-EU websites with a low (high) EU user share have a lower (higher) incentive to voluntarily comply with GDPR for their non-EU users. However, we note that GDPR's effect could also be stronger for non-EU websites with a small EU user share.

Voluntary GDPR compliance by the control group would yield a weaker observed GDPR effect because it makes the behavior in the treatment and control groups more similar. Interestingly, the GDPR estimate for websites with low and high EU user shares becomes stronger 18 months post-GDPR. The difference between non-EU websites with low and high EU user shares also diminishes, indicating that the differences in voluntary compliance decrease over time. This finding could mean that websites with high (low) EU user shares voluntarily comply less (more) with the GDPR over time.

This finding aligns with other GDPR research. For example, Johnson et al. (2023) studied the GDPR's impact on web technology vendors and found that a spillover effect from the EU to US users dissipated four months post-GDPR. Our finding is also consistent with anecdotal evidence from Nicolosi (2022), who states that "*with minimal EU contacts, U.S.-based businesses will naturally feel inclined to avoid GDPR compliance if they can do so.*" Additionally, non-EU websites are only subject to GDPR if they target EU users. Confusion about interpreting what it means to "target" EU users—which the European Data Protection Board clarified in November 2018— may explain the disappearance of a spillover effect for non-EU websites with a high EU user share over time.

- 2. Alternative Matching Criteria: We adjust our GSC specification by no longer using industry as a matching variable for the treatment and control website-instances. Instead, we require the potential control website-instances to belong to a website with a similar EU share of users for its treated website-instance as the focal treatment website-instance. We find no significant difference in the 3-month and 18-month post-GDPR effect between our main GSC specification and this alternative specification (see Web Appendix H).
- 3. Comparison of User Behaviors: We compare the effect of GDPR on the browsing behavior of treated non-EU users on EU websites (Cell 2 in Figure 1) to untreated non-EU users on non-EU websites (Cell 4). Additionally, we compare the effect on treated EU users on non-EU websites (Cell 3) to untreated non-EU users on non-EU websites (Cell 4). A spillover effect will become

apparent if the behavior of treated users does not differ from that of untreated users in the control group.

We find that non-EU users use treated EU websites less post-GDPR than pre-GDPR, while they use untreated non-EU websites more. Similarly, treated EU users use non-EU websites less post-GDPR, whereas untreated non-EU users use non-EU websites more. While these indicate changes in user behavior (see Web Appendix E), they do not entirely rule out the possibility of a spillover effect but suggest that any such effect is limited in magnitude.

- 4. **Manual Inspection:** A manual inspection of a subsample of control websites concerning their non-EU user interface indicates no voluntary compliance by these websites⁸.
- 5. Difference-in-Differences Analysis: In Web Appendix I, we conduct a DID analysis with a sub-sample of our data consisting of websites for which we observe both treatment and control website-instances. We compare non-EU website-instances with EU users (Cell 3) in the treatment group to non-EU website-instances without EU users (Cell 4) in the control group. This approach eliminates website differences between groups. We find slightly stronger GDPR effects on weekly visits.

We interpret these slightly stronger estimates as evidence of a limited spillover effect. If a strong spillover effect existed, we would expect smaller differences between the treatment and control groups in Figure 5, resulting in a weaker GDPR effect. Instead, the consistently stronger GDPR effect in our DID analysis compared to our main estimates suggests that any spillover effect is not substantial.

Although we cannot entirely rule out that non-EU websites targeting non-EU users may have voluntarily complied with the GDPR, potentially contaminating our control group, our analyses

⁸ We caution, however, that other unobservable factors could easily spill over from EU to non-EU users. Such unobservable factors could include other technology changes beyond observable changes in user interfaces, such as changes to hosting vendors or audience measurement tools. Although such unobservable factors may spill over from the treatment to the control group, they would only affect our GDPR effect if users' browsing behavior were affected by these technology changes.

indicate that any such spillover effect is limited. Similarly, non-EU users could have adapted their behavior on non-EU websites due to awareness of the GDPR, independent of whether non-EU websites voluntarily adjusted their interfaces. In such cases, we cannot entirely dismiss spillovers from the treatment to the control group.

In conclusion, while spillover effects from the treatment to the control group may exist, our robustness tests—consistent with other GDPR research (e.g., Johnson et al. 2024; Peukert et al. 2022)—indicate that any such effect is of limited magnitude and diminishes over time. Our robustness results show some evidence of a spillover 3 months post-GDPR, but this effect vanishes 18 months post-GDPR. Therefore, if a spillover effect exists, our reported main results would likely underestimate, rather than overestimate, the actual impact of the GDPR's enactment.

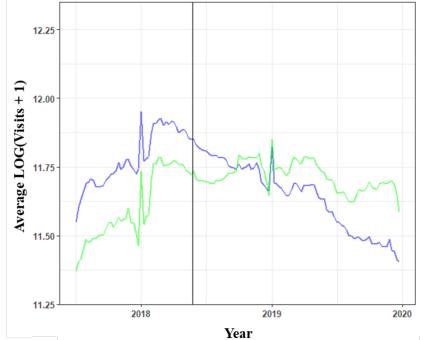
Related to voluntary GDPR compliance of the control group is the possibility of deliberate GDPR non-compliance by the treatment group. Such non-compliance could occur if, pre-GDPR, websites originally based in the EU decided to relocate to a non-EU location to avoid complying with GDPR for non-EU users. Such strategic shifts would reduce the suitability of our control group, as some websites would belong to the control instead of the treatment group. To examine this, we recalculated GDPR's effect on our main metric for a subsample with a stricter control group that includes only websites with domain suffixes indicating a non-EU location. Web Appendix E shows no significant difference in GDPR's effect when comparing our main estimates with those using the stricter control group.

Unconfoundedness: The fourth assumption is that GDPR did not coincide with other major changes in potentially confounding factors. In Web Appendix G, we investigate whether substantial changes occurred in factors such as internet speed, the share of the population with internet access, laptop, and smartphone usage for non-EU and EU users. We found no evidence of differences between the user groups in the pre-and post-GDPR periods across these factors that could substantially influence the control group's user behavior. Nonetheless, as with most empirical research inferring causal effects from non-experimental data, we cannot entirely rule out the existence

of contemporaneous unobservable factors that may confound our GDPR effect. Such factors may include changes in website technology, such as changes in hosting vendors or audience measurement tools, that could spill over from EU to non-EU users.

In summary, we thoroughly examined our identifying assumptions and concluded that they are justified. Although a potential spillover effect may exist, it is likely small, as our robustness results are directionally consistent with our main results. Moreover, any potential spillover effect dissipates 18 months post-GDPR. Therefore, our estimated effect would, if anything, underestimate GDPR's actual impact because the treatment might also affect the control group. Furthermore, our estimated GDPR effect, including the spillover effect, is policy-relevant because it measures the disadvantage of treated websites relative to untreated websites, capturing the comparative impact of the GDPR.

Figure 5: Average Weekly LOG(Visits + 1) for Non-EU Websites with EU User Traffic (Treatment Group) and Non-EU Websites with Non-EU User Traffic (Control Group)



Notes: Blue Line = Treatment Group Average Weekly log(Visits + 1). Green Line = Control Group Average Weekly log(Visits + 1). Black Vertical Line = Enactment date of GDPR (May 25th, 2018).

Support for the Robustness of our Choice of Generalized Synthetic Control (GSC) Estimator

We used the GSC estimator proposed by Xu (2017) and implemented in the gsynth R package to obtain our results. To test robustness, we re-calculated GDPR's effect on our main metric, weekly visits, using the original synthetic control estimator proposed by Abadie and Gardeazabal (2003) and Abadie et al. (2010, 2011, 2014) implemented in the synth R package. Web Appendix H shows no significant difference in the estimated effects between both estimators, indicating that our results are robust to the choice of the synthetic control estimator.

ANALYSIS OF GDPR'S ECONOMIC EFFECT ON WEBSITES

While our study focused on quantifying GDPR's effect on online usage behavior, understanding how GDPR impacted a firm's revenue is also crucial for policymakers, given potential negative societal effects. In this section, we provide a back-of-the-envelope estimation of the possible economic effects on websites resulting from changes in usage behavior due to the GDPR. We use the GDPR's average effect after 18 months as the basis for our calculations and present two estimations corresponding to websites that earn revenue (i) by selling products (e-commerce websites) and (ii) by displaying advertisements.

Analysis of the GDPR's Economic Effect on E-Commerce Websites

For the e-commerce websites in our sample, the average drop in visits at 18 months post-GDPR amounted to 3.37% (Table W 1 in Web Appendix A). We determine the revenue of an e-commerce website by multiplying the number of visits (i.e., non-unique visitors), the conversion rate (i.e., the proportion of visits resulting in a purchase), and the revenue per purchase:

(6) Revenue = Visits * Conversion Rate * Revenue per Purchase

Based on the Q1 2020 e-commerce benchmarks by Monetate (2020), the revenue per purchase globally is \$105.99, and the average conversion rate per visit is 1.91%. Looking at the e-commerce websites in our sample, the average yearly visits across all countries amounted to 70,461,862. Therefore, the average yearly revenue for an e-commerce website in our study pre-GDPR is:

(7) $Revenue_{avg.} = 70,461,862 * 1.91\% * \$105.99 = \$142,643,623.54.$

The average drop in visits over 18 months (1.5 years) post-GDPR represents the respective decline in revenue:

(8) Revenue Change_{18 months} = -3.37% * \$142.643.623,54 * 1.5 = -\$7,209,722.73.

Thus, a 3.37% decrease in visits due to GDPR could reduce the revenue of an average e-commerce website by over \$7 million in the first 18 months post-GDPR. Our estimated impact of the GDPR on e-commerce revenues is larger because it includes the reductions in revenue driven by a broader range of factors, including changes in user website visit behavior and other marketing channels beyond those examined by Goldberg et al. (2024).

Analysis of GDPR's Economic Effect on Ad-Based Websites

For ad-based websites, we determine revenue by multiplying the number of page impressions, the number of ads displayed per page impression, and the price per ad impression:

(9) Revenue = Page Impressions * Ads per Page Impression * Ad Price

Using the News and Media industry as an example, the average yearly page impressions per website in our sample across all regions are 358,859,344. A random sample of the homepages and article pages of seven major news websites (nytimes.com, huffpost.com, washingtonpost.com, news.yahoo.com, bbc.com, wsj.com, and cnn.com) showed an average of 7.6 ads per page. Based on industry reports (ComScore 2010, TheBrandOwner 2017), the average CPM (cost per thousand ad impressions) for news websites is between \$7 and \$8 (here, we use \$0.0075 per impression). Therefore, the average yearly revenue for a news website pre-GDPR is:

(10) $Revenue_{avg.} = 358,859,344 * 7.6 * \$0.0075 = \$20,454,982.61.$

The GDPR's average effect on page impressions after 18 months for our sample of news and media websites was a drop of 8.05%. This decline results in a decrease in revenue of almost \$2.5 million (or 12.08%) in the first 18 months post-GDPR:

(11) Revenue Change_{18 months} = -8.05% * \$20,454,982.61 * 1.5 = -\$2,469,953.43.

Again, our estimate is similar in direction but somewhat higher than the result of Goldberg et al. (2024), who found that, four months after the GDPR, ad-based websites lost up to 6.10% in revenue.

SUMMARY, CONCLUSIONS, AND IMPLICATIONS

Summary

In our study, we analyze the impact of the General Data Protection Regulation (GDPR) on online user behavior, using data from 6,286 websites in the United States and Europe across 24 industries over 18 months post-GDPR. Our coverage of over 1.15 trillion website visits from the EU and 1.8 trillion from the US makes our study one of the most extensive studies on this topic. Our results indicate that the GDPR hurt user quantity, making the effect more pronounced over time. In the short term (3 months post-GDPR), weekly visits per website dropped by 4.88%, while in the long term (18 months post-GDPR), the decrease reached 10.02%. These results highlight the importance of tracking GDPR's effects over an extended period to capture its full impact.

Interestingly, the results for usage intensity metrics—how engaged users were on the websites—were more nuanced. Websites that gain (lost) users suffered (benefited) from an increasing (decreasing) impact on user engagement. These findings suggest that the GDPR has created two major challenges for websites: they either struggle to attract users or retain their engagement.

Additionally, these negative effects differ across websites. Smaller websites and those in specific industries were more significantly affected, while a few websites even benefited from GDPR. Our analysis demonstrates how to estimate the economic damage for websites, revealing average revenue losses of approximately \$7 million for e-commerce websites and \$2.5 million for ad-based websites over 18 months post-GDPR.

Our study also examines the heterogeneity of GDPR's impact based on website characteristics—such as industry and size—and a user characteristic, namely the user's country of origin. We find that GDPR's effect varied significantly across industries, with sectors like "Heavy Industry and Engineering" and "Gambling" experiencing the most substantial declines. Smaller websites suffered more negative effects than larger ones, indicating a potential increase in market concentration post-GDPR. The impact also differed based on users' countries, reflecting cultural differences in privacy concerns.

These and the other results rest upon the assumption that our control group was unaffected by GDPR. While we find substantial support for this assumption, particularly when analyzing data 18 months post-GDPR, it is important to acknowledge potential limitations. Specifically, a moderate spillover effect may have occurred during the earlier stages of GDPR implementation (within the first 3 months post-GDPR), particularly for websites with a high share of EU users. As a result, our estimates could represent a lower bound of GDPR's true effect, reflecting the disadvantage faced by treated (EU) websites compared to untreated (non-EU) websites.

Moreover, a potential source of measurement error arises from non-consenting users post-GDPR. The regulation allows users to decline consent for data collection, which could create discrepancies between actual and recorded online user behavior. Researchers have addressed this challenge in various ways. For instance, Goldberg et al. (2024) use a selection model with several assumptions to account for non-consenting users. Lefere et al. (2024) rely on data from Alexa, which gathers web traffic data from various sources, not relying on cookies, such as users of its Alexa Toolbar and over 25,000 other browser extensions.

Our study adopts a similar approach to Lefrere et al. (2024) by using data from SimilarWeb. SimilarWeb aggregates user data from its browser extension (with approximately 1 million users) and first-party web analytics data (such as from Google Analytics). It produces estimated online user behavior data and accounts for non-consenting users (see Web Appendix F for further details). We find that user behavior data from SimilarWeb leads to results similar to those obtained using a selection model, supporting the robustness of our findings.

Conclusions

Our findings provide an important assessment of how GDPR has altered user interactions with websites and the financial outcomes for businesses. These insights help predict the effects of similar regulations in other regions or sectors. By analyzing the economic and behavioral consequences of GDPR, our results could aid in refining privacy legislation to balance user rights with business sustainability.

A critical aspect of our results is the complexity of user behavior in response to GDPR. The shifts in online engagement reflect how users react to changes in privacy policies and consent mechanisms, such as data collection banners. Users' perceptions of the costs and benefits of engaging with websites under the new privacy rules drive these decisions. While our study shows a decline in user quantity and engagement for many websites, overall internet usage is unlikely to decline due to GDPR or similar privacy regulations. Instead, users are reallocating their online activity, spending more time on websites they trust or perceive as offering greater value under the new privacy landscape.

This reallocation of time aligns with the sunk-cost effect (Arkes and Blumer, 1985). The sunkcost theorem posits that users are more likely to engage with services where they perceive they have already "paid" a cost—whether financial or in the form of data. In the context of GDPR, users may become more aware of the "cost" they pay with their personal data, leading them to prefer websites where they have already provided data or those they perceive as more trustworthy. This reallocation behavior, although outside the direct scope of this research, presents an avenue for further study into the mechanisms behind user decision-making and their responses to privacy regulations.

Our findings also highlight a clear trade-off between privacy and profits. While GDPR strengthens privacy protections, it also imposes costs on businesses, particularly those reliant on datadriven revenue models. This tension between safeguarding user privacy and maintaining business profitability demonstrates the challenges of balancing regulatory goals and the economic realities of online businesses.

The study underscores the importance of a long-term perspective when evaluating GDPR's impact. The effects increase over time, with user engagement declining well into the second year post-GDPR. This long-term impact suggests that short-term evaluations may underestimate the full

scope of privacy regulations, emphasizing the need for sustained observation to capture the complete effects.

Moreover, our results show that not all websites were equally affected. Smaller websites and those in specific industries experienced greater difficulties, while some larger or more established websites saw positive outcomes. The initial privacy norms in different countries may partly explain this heterogeneity in the impact of GDPR. Websites operating in regions with stricter pre-existing privacy protections experienced less disruption than those in more permissive environments.

The lack of a rebound effect, where websites might recover as they adapt to the new regulations, contrasts with other studies' findings (e.g., Lefrere et al. 2024). In our data, the negative effects persisted, suggesting that the challenges introduced by GDPR may be longer-lasting than previously thought.

Finally, the observed reallocation of user activity shows that users are redistributing their online presence rather than leaving the internet altogether. As GDPR alters the digital landscape, businesses must adapt to the changing patterns of user engagement.

In conclusion, GDPR has had a heterogeneous and evolving impact on online user behavior, with significant consequences for businesses and users. While its average effect has been negative regarding user quantity and engagement, certain websites have benefited from the increased focus on privacy. Understanding this complexity is essential for shaping future privacy laws and for businesses navigating the evolving regulatory environment. Further research into the underlying behavioral mechanisms driving these outcomes offers promising opportunities to deepen our understanding of privacy regulation's long-term effects.

Implications

The results of this study carry significant implications for several key stakeholders in the online advertising market, including publishers, advertisers, users, and regulators. Each group faces unique challenges and opportunities in light of GDPR's effects on user behavior and website economics. *Implications for publishers*. GDPR has particularly affected publishers because the publishers' business models often rely on collecting and processing user data to generate revenue through advertising. Our findings indicate that smaller websites, in particular, experienced greater declines in user engagement, underscoring the financial vulnerability of these businesses.

However, GDPR also allows publishers to build trust with their audiences. Publishers can differentiate themselves in a competitive market by embracing transparency and ensuring robust compliance with privacy regulations. Websites that communicate their data practices and offer users more control over their privacy will likely foster greater loyalty and long-term engagement.

To mitigate the negative impact of reduced ad revenues, publishers may need to diversify their revenue streams, exploring alternatives such as subscription models, premium content, or contextual advertising—which respects user privacy by targeting ads based on content rather than personal data.

Implications for advertisers. For advertisers, GDPR has imposed significant limitations on data collection and targeting, particularly for personalized advertising. Our study shows that many addriven websites faced substantial revenue losses due to these restrictions. Advertisers will need to adapt by rethinking their approach to user data.

One promising avenue is the shift towards privacy-first advertising models, such as contextual advertising, where ads are shown based on the content of the webpage rather than detailed user data. This strategy allows advertisers to reach relevant audiences without infringing on privacy regulations. Moreover, advertisers that succeed in gaining user consent for data collection may still be able to conduct targeted campaigns, albeit to a smaller but more engaged audience.

Advertisers should also invest in first-party data collection methods, building stronger relationships with users who voluntarily share their information in exchange for personalized services. This approach will be vital to maintaining relevance in the post-GDPR advertising landscape.

Implications for users. GDPR has empowered users by giving them greater control over their personal data. Our study shows that while GDPR has negatively impacted user quantity on many

websites, overall internet usage is unlikely to decline. Instead, users are likely to reallocate their online activity, spending more time on websites they trust and perceive as offering more value under the new privacy regulations.

This shift is compatible with the sunk-cost effect, where users prefer to continue engaging with websites to which they have already provided their data, rather than starting fresh with new platforms. Users are now more aware of the "cost" of using free services—i.e., the exchange of personal data—and are making more informed decisions about which websites to engage with.

While consent mechanisms and cookie banners have introduced some friction in the user experience, the increased awareness and control that users now have over their data represents a net positive. Moving forward, platforms that streamline these consent processes while respecting privacy will likely win user trust and engagement.

Implications for regulators. For regulators, GDPR has been a landmark in privacy protection, setting a global standard influencing data policies worldwide. However, the results of this study suggest that enforcement and compliance remain critical areas for further consideration. Websites in regions with stricter enforcement or more robust compliance frameworks faced greater challenges, highlighting the need for regulatory approaches that are both consistent and adaptable to different contexts.

Our findings also underscore the heterogeneous impact of GDPR across websites and industries, suggesting that a one-size-fits-all approach to privacy regulation may not be appropriate. Policymakers should consider sector-specific guidelines to ensure privacy protections do not disproportionately burden smaller businesses or stifle innovation.

Furthermore, as other regions adopt GDPR-like regulations, international collaboration between regulators will be crucial to creating user-centric, harmonized privacy standards that support global commerce. The ongoing refinement of these regulations, as informed by studies such as this one, can help balance protecting user privacy and fostering innovation in the digital economy.

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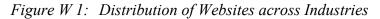
The Impact of the General Data Protection Regulation

(GDPR) on Online User Behavior

Web Appendix

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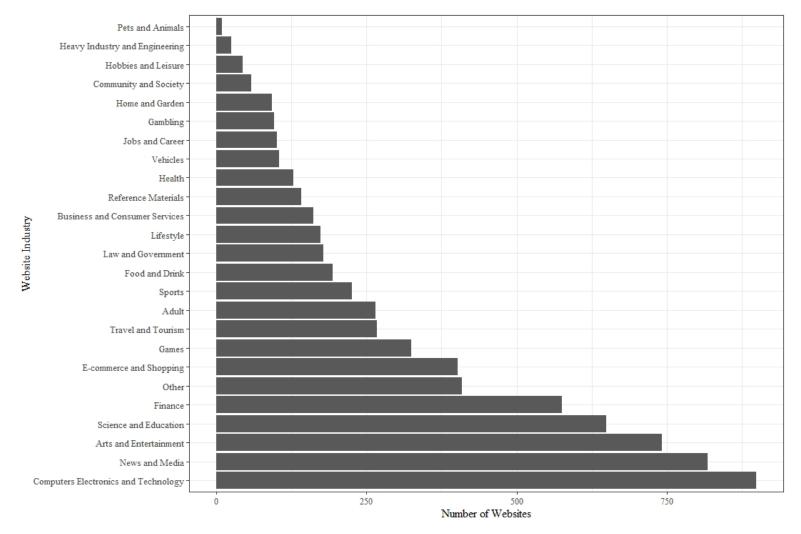


Figure W 2 shows the distribution of GDPR's effect on the websites' monthly unique visitors over different post-treatment periods.

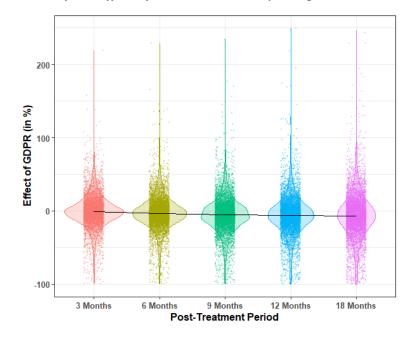
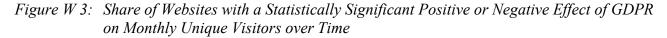
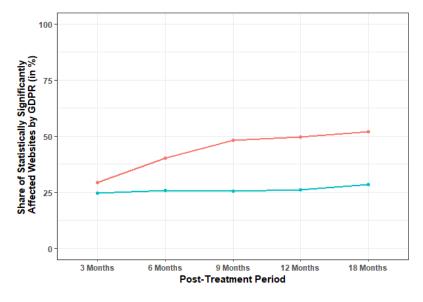


Figure W 2: Distribution of the Effect of GDPR on Monthly Unique Visitors over Time

Figure W 3 shows the share of websites with a statistically significant positive or negative effect of GDPR on the monthly unique visitors over time. The red line plots the share of websites that GDPR affected statistically significantly negatively (p < .05), and the blue line plots the share of websites that GDPR affected statistically significantly positively (p < .05).





🔸 Share of sig. negatively affected websites 😁 Share of sig. positively affected websites

Figure W 4 shows the distribution of GDPR's effect on the websites' weekly page impressions over different post-treatment periods.

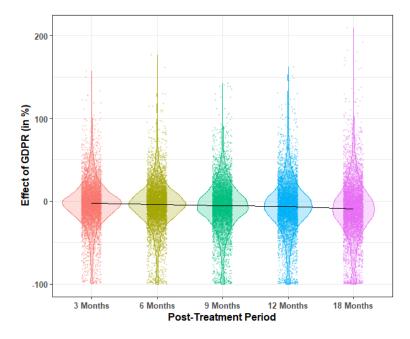
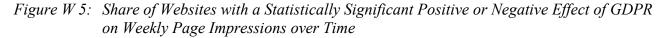
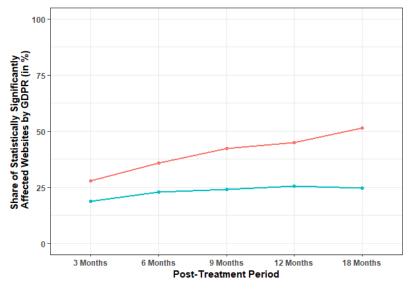


Figure W 4: Distribution of GDPR's Effect on Weekly Page Impressions over Time

Figure W 5 shows the share of websites with a statistically significant positive or negative effect of GDPR on the weekly page impressions over time. The red line plots the share of websites that GDPR affected statistically significantly negatively (p < .05), and the blue line plots the share of websites that GDPR affected statistically significantly positively (p < .05).





🔸 Share of sig. negatively affected websites 😁 Share of sig. positively affected websites

Industry		Post	-Treatment	Period	
	3 months	6 months	9 months	12 months	18 months
Business and Consumer Services	4.31%	5.56%	2.29%	-0.23%	-1.57%
Travel and Tourism	3.13%	0.83%	-1.91%	-3.10%	-2.10%
Vehicles	1.80%	5.26%	3.41%	3.51%	3.85%
E-commerce and Shopping	0.14%	-0.70%	-2.41%	-3.14%	-3.37%
Law and Government	-0.24%	-1.06%	-0.70%	-0.89%	-2.55%
Sports	-0.80%	-2.95%	-4.67%	-5.71%	-9.45%
Food and Drink	-1.17%	-4.00%	-3.80%	-2.07%	-0.16%
News and Media	-1.36%	-6.12%	-8.66%	-8.69%	-7.67%
Science and Education	-1.36%	-5.57%	-8.06%	-8.37%	-9.13%
Jobs and Career	-2.07%	-1.82%	-3.57%	-4.15%	-5.50%
Community and Society	-2.52%	-5.64%	-1.17%	3.85%	4.69%
Health	-2.86%	-8.72%	-11.71%	-13.83%	-15.15%
Finance	-3.85%	-5.51%	-6.66%	-6.42%	-4.56%
Adult	-4.06%	-8.46%	-10.88%	-11.09%	-9.69%
Home and Garden	-6.06%	-4.69%	-4.24%	-4.31%	-4.45%
Computers, Electronics and Technology	-6.51%	-8.40%	-10.59%	-11.96%	-14.80%
Hobbies and Leisure	-7.33%	-7.17%	-8.48%	-9.30%	-9.92%
Reference Materials	-7.74%	-9.90%	-10.16%	-8.90%	-7.96%
Arts and Entertainment	-8.03%	-10.36%	-12.47%	-13.14%	-12.50%
Games	-8.43%	-10.02%	-11.14%	-11.96%	-13.81%
Lifestyle	-9.04%	-9.44%	-11.32%	-11.67%	-13.79%
Gambling	-19.17%	-17.20%	-12.12%	-9.72%	-7.38%
Other	-27.95%	-32.86%	-37.54%	-39.22%	-42.62%
Heavy Industry and Engineering	-46.41%	-49.84%	-49.55%	-49.35%	-44.76%

Table W1: Distribution of GDPR's Effect on Weekly Visits across Industries

Notes: This table shows the distribution of the average effect of GDPR (in %) on the weekly visits per website across industries and post-treatment periods. The 3-month post-GDPR effect orders the rows in the table in descending order.

Reading example: In the second row, the value of -1.57% in the last column means that, on average, GDPR decreased the weekly visits per website in the Business and Consumer Services industry by 1.57% 18 months post-GDPR's enactment.

	Post-Treatment Period					
Industry Rank Decile	3 months	6 months	9 months	12 months	18 months	
1	-3.74%	-5.60%	-7.56%	-8.50%	-9.04%	
2	-2.02%	-3.78%	-5.43%	-6.06%	-6.49%	
3	-2.26%	-3.70%	-5.15%	-5.63%	-5.82%	
4	-2.96%	-4.76%	-5.89%	-5.33%	-6.55%	
5	-1.82%	-4.08%	-5.86%	-6.57%	-7.25%	
6	-4.30%	-6.46%	-8.64%	-9.37%	-10.39%	
7	-6.23%	-8.89%	-10.89%	-11.29%	-11.51%	
8	-6.21%	-8.47%	-10.29%	-10.63%	-11.31%	
9	-5.41%	-8.22%	-10.62%	-10.74%	-10.31%	
10	-13.89%	-18.29%	-20.38%	-20.55%	-21.49%	
Top 50%	-2.56%	-4.38%	-5.98%	-6.42%	-7.03%	
Botton 50%	-7.21%	-10.07%	-12.16%	-12.52%	-13.00%	

Table W 2: Distribution of GDPR's Effect on Weekly Visits across Deciles of Industry Rank

Notes: This table shows the distribution of the average effect of GDPR (in %) on the weekly visits per website across deciles of industry rank and post-treatment periods. The 10% largest websites pre-GDPR (i.e., the ones with the lowest rank numbers) worldwide, across all countries and industries, are part of the 1st decile, while the 10% smallest websites pre-GDPR are part of the 10th decile.

Reading example: In the second row, the value of -3.74% in the second column means that, on average, GDPR reduced the weekly visits across the largest (i.e., those in the top-decile) websites in each industry by -3.74%. The results of the top-decile reflect the change of the 10% largest websites 3 months post-GDPR's enactment.

	Post-Treatment Period					
Users' Country of Origin	3 months	6 months	9 months	12 months	18 months	
Denmark	-1.06%	-4.43%	6.26%	-7.12%	-6.97%	
Poland	-2.27%	-3.31%	-4.04%	-4.74%	-5.55%	
Germany	-2.87%	-5.11%	-6.60%	-6.84%	-6.55%	
Italy	-3.00%	-6.47%	-8.64%	-9.06%	-9.37%	
Spain	-3.06%	-5.06%	-7.33%	-8.28%	-8.02%	
United States	-3.28%	-6.27%	-8.48%	-8.80%	-9.78%	
France	-4.25%	-5.58%	-8.74%	-9.10%	-9.82%	
Switzerland	-5.55%	-7.55%	-9.76%	-10.77%	-12.20%	
Hungary	-7.28%	-10.32%	11.86%	-12.08%	-11.80%	
Netherlands	-7.28%	-12.23%	-15.25%	-15.71%	-17.20%	
United Kingdom	-7.47%	-8.74%	-10.49%	-10.96%	-12.57%	
Sweden	-7.90%	-9.32%	-11.47%	-12.13%	-13.36%	
Austria	-8.45%	-9.09%	-10.22%	-10.16%	-9.21%	

Table W 3: Distribution of GDPR's Effect on Weekly Visits across Users' Country of Origin

Notes: This table shows the distribution of the average effect of GDPR (in %) on the weekly visits per website across users' country of origin and post-treatment periods. The 3-month post-GDPR effect orders the rows in the table in descending order.

Reading example: In the second row, the value of -1.06% in the second column means that, on average, GDPR reduced the weekly visits from Denmark by 1.06% 3 months post-GDPR's enactment.

Every usage intensity metric is a function of two user quantity metrics. For example, we calculate in Equation (W1) the visits per unique visitor on a website w by dividing the visits on website w by the unique visitors on website w; page impressions per visit follow the same logic in Equation (W2):

(W1) Visits per Unique Visitor_w =
$$\frac{Visits_w}{Unique Visitors_w}$$

(W2) Page Impressions per Visit_w = $\frac{Page Impressions_w}{Visits_w}$

We use Equations (W1) and (W3) to examine GDPR's effect on the usage intensity metrics in the following manner:

- We use Equation (1) to calculate GDPR's effect (Δ) for all user quantity metrics. Our methodology to derive this effect, Δ, captures the relative changes of each user quantity metric for each website *w* and each post-treatment period *p*.
- 2) We then incorporate GDPR's effect, Δ, for all the metrics for each post-treatment period p in Equations (W1) and (W4). As we capture the relative changes for the metrics, we can incorporate GDPR's effect, Δ, for each post-treatment period p for each website w by multiplying the metrics' pre-treatment values with (1 + Δ_{p,w}).
- Finally, we rearrange the equations to isolate GDPR's effect, Δ, on the usage intensity metric of interest.

We now use the described process to derive GDPR's effect on "Visits per Unique Visitor". The "Page Impressions per Visit" can be derived accordingly. We begin by incorporating GDPR's effect, Δ , for post-treatment period *p* for website *w* for all metrics within Equation (W1):

(W5) $Visits_{p,w} = Visits_w * (1 + \Delta Visits_{p,w})$

(W6) Unique Visitors_{p,w} = Unique Visitors_w * $(1 + \Delta Unique Visitors_{p,w})$

(W7) Visits per Unique Visitor_{p,w} = Visits per Unique Visitor_w * $(1 + \Delta Visits per Unique Visitor_{p,w})$

Incorporating GDPR's effect Δ (Equations (W5)-(W7)) into Equation (W1) yields:

(W8) Visits per Unique Visitor_{p,w} = $\frac{Visits_{p,w}}{Unique Visitor_{p,w}}$

 $(W9) Visits per Unique Visitor_{w} * (1 + \Delta Visits per Unique Visitor_{p,w}) = \frac{Visits_{w} * (1 + \Delta Visits_{p,w})}{Unique Visitors_{w} * (1 + \Delta Unique Visitor_{p,w})}$

Rearranging Equation (W9) leads to:

$$(W10) \ 1 + \Delta Visits \ per \ Unique \ Visitor_{p,w} = \frac{Visits_w * (1 + \Delta Visits_{p,w})}{Unique \ Visitors_w * (1 + \Delta Unique \ Visitors_{p,w}) * Visits \ per \ Unique \ Visitor_w}$$
$$(W11) \ \Delta Visits \ per \ Unique \ Visitor_{p,w} = \frac{Visits_w * (1 + \Delta Unique \ Visitors_{p,w})}{Unique \ Visitors_w * (1 + \Delta Unique \ Visitors_{p,w}) * Visits \ per \ Unique \ Visitor_w} - 1$$
$$(W12) \ \Delta Visits \ per \ Unique \ Visitor_{p,w} = \frac{Visits_w}{Unique \ Visitors_w} * \frac{1}{Visits \ per \ Unique \ Visitors_{p,w}}} - 1$$

Replacing the Visits per Unique Visitor_w in Equation (W13) by Equation (W12) yields: (W14) ΔV is the per Unique Visitor_{p,w} = Visits per Unique Visitor_w * $\frac{1}{Visits per Unique Visitor_w}$ * $\frac{1 + \Delta Visits_{p,w}}{1 + \Delta Unique Visitor_{p,w}} - 1$

Finally, rearranging Equation (W13) yields:

(W15)
$$\triangle$$
 Visits per Unique Visitor_{p,w} = $\frac{1 + \Delta$ Visits_{p,w}}{1 + \Delta Unique Visitor_{p,w} - 1

In Equation (W14), we determine GDPR's effect on the visits per unique visitor based on the observed GDPR effect on the corresponding user quantity metrics, i.e., visits and unique visitors. We use Equation (W14) to determine GDPR's effect on the visits per unique visitor – and, in the same manner, for the other usage intensity metrics, page impressions per visit – for each website and each post-treatment period p (i.e., a period that covers 3, 6, 9, 12, and 18 months post-GDPR's enactment).

WEB APPENDIX C: ROBUSTNESS CHECKS CONCERNING WEBSITE SELECTION

In our analysis, we selected a threshold of an average of 1,000 weekly visits for our sample. So, we removed all websites with average weekly visits below this threshold (Step 2 in Table 8). As the threshold selected might affect our results, we compare GDPR's effect obtained from a sample with and without the threshold to examine the impact on the results.

We summarize GDPR's effect on weekly visits for our original sample with the selection threshold and our newly obtained sample without the selection threshold in Table W 4. Removing the website selection threshold decreases GDPR's effect in all post-GDPR enactment periods, except for the 3-month effect (p < .05). For example, instead of reducing the weekly visits in our original sample by 10.02% (18 months post-GDPR), it reduces them in the sample without the threshold by 11.80%. Thus, our results change statistically significantly when removing the threshold of 1,000 weekly visits. As the effect becomes stronger, our main result seems to be a conservative estimate of GDPR's effect, likely due to low-trafficked websites experiencing stronger negative effects than more-trafficked websites as in our original sample.

Table W 4: Summary of GDPR's Effect on Weekly Visits with and without Using the Thresholdfor Website Selection of 1,000 Average Weekly Visits

			Post-Treatment Period				
		3 months	6 months	9 months	12 months	18 months	
Original Sample Obtained with Selection	Mean:	-4.88%	-7.22%	-9.07%	-9.57%	-10.02%	
Threshold	Median:	-3.49%	-5.54%	-7.54%	-8.24%	-8.91%	
(N=9,683)							
New Sample Obtained without Selection	Mean:	-5.77%	-8.51%	-10.66%	-11.31%	-11.80%	
Threshold	Median:	-4.02%	-6.03%	-8.29%	-8.92%	-9.90%	
(N=11,760)							
p-value of t-test:	1	0.070	0.009**	0.002**	0.001***	0.004**	

Significance level: *** 0.1%-level ** 1%-level * 5%-level. Note: The original sample is obtained after the removal of duplicated websites (Step 1 in Table 1), website-instances with average weekly visits < 1,000 (Step 2), and website-instances with zero visits in at least one month or strong outliers (Step 3). The new sample without a selection threshold is obtained by only performing Step 1 and Step 3 but omitting Step 2 in Table 1.

WEB APPENDIX D: ROBUSTNESS CHECKS CONCERNING EARLY AND LATE COMPLIANCE

Table W 5:	Weekly Visits with and withou	t 30-Day-Period pre- and post-GDPR

Weekly	Original	Results	Robustne	ess Results		
Visits	(entire observ	ation period)	(omitting 30 days p	re- and post-GDPR)		
	Median	Mean	Median	Mean		
	-3.49%	-4.88%	-4.55%	-5.49%		
3 months	No significar	obustness results				
	-5.54%	-7.22%	-6.38%	-7.91%		
6 months	p-value of t-test: 0.17 No significant difference between the original and robustness results					
	-7.54%	-9.07%	-8.24%	-9.74%		
9 months	p-value of t-test: 0.20 No significant difference between the original and robustness results					
	-8.24%	-9.57%	-8.78%	-10.09%		
12 months	p-value of t-test: 0.35 No significant difference between the original and robustness results					
	-8.91%	-10.02%	-9.56%	-10.30%		
18 months	No significar	-	e of t-test: 0.65 een the original and re	obustness results		

Significance level: *** 0.1%-level ** 1%-level * 5%-level

In our control group, we use website-instances of non-EU websites with non-EU users (see Cell 4 in Figure 1). However, there is a concern about a spillover effect of the GDPR on these instances, which are technically outside of the regulation's scope. For example, non-EU websites with users from EU locations must comply with the GDPR for those users. Differentiating between EU and non-EU users might be more costly than uniformly applying GDPR compliance to all users, including non-EU users. Consequently, some websites might voluntarily extend GDPR compliance to non-EU users—a phenomenon known as the "Brussels effect" (Peukert et al. 2022).

To address this concern, we conduct five robustness checks:

- Comparison Based on EU User Share: We compare control websites with small and large shares of EU users to test if those with a larger share are more likely to comply with the GDPR voluntarily.
- 2) Non-EU User Behavior on EU vs. Non-EU Websites: We compare the behavior of non-EU users on EU websites (Cell 2 in Figure 1) versus non-EU websites (Cell 4).
- EU vs. Non-EU users on Non-EU Websites: We compare the behavior of EU users (Cell 3) and non-EU users (Cell 4) on non-EU websites.
- 4) User Interface Changes Post-GDPR: We examine visible changes in the user interface for untreated non-EU users post-GDPR on a subsample of non-EU websites.
- Assessment of Strategic Shifts: We assess whether treated websites based in the EU shifted their geographic location post-GDPR to evade compliance, potentially affecting the treatment and control groups.

Voluntary Compliance Based on EU User Share

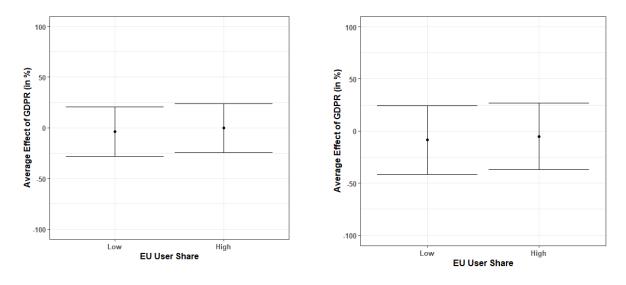
Websites might find it too costly to treat EU and non-EU users differently and, therefore, voluntarily comply with the GDPR for all users. Such voluntary compliance is more likely for non-EU websites with a high share of EU users. This behavior aligns with Nicolosi (2022), who notes that U.S.-based businesses with minimal EU contacts may avoid GDPR compliance.

In this robustness check, we compare the GDPR's average 3-month effect on weekly visits between websites with high and low EU user shares. 3 months post-GDPR, Figure W 10 shows that GDPR's effect is stronger for websites with a low EU user share (p = 0.01). Notably, the significant difference between these groups disappears 18 months post-GDPR (p = 0.08).

This finding suggests that non-EU websites with a low EU user share have less incentive to voluntarily comply with the GDPR, resulting in a stronger observed effect. For websites with a high

EU user share, voluntary compliance seems to diminish over time as GDPR's effect becomes stronger 18 months post-enactment.

Figure W 6: GDPR's Average 3 (left panel) and 18 (right panel)-Month Effect on Weekly Visits by Groups of Non-EU Websites with High and Low Shares of EU User Traffic



Notes: GDPR's effect for websites with low EU user share: Mean -3.85% (SD: 24.34%). GDPR's effect for websites with high EU user share: Mean: -0.17 (SD: 24.16%). The average difference is significant in a two-sample t-test (t = -2.46, df = 917.68, p-value = 0.01).

Notes: GDPR's effect for websites with low EU user share: Mean -8.58% (SD: 32.84%). GDPR's effect for websites with high EU user share: Mean: -5.05% (SD: 31.78%). The difference in means is not significant in a two-sample t-test (t = -1.76, p-value = 0.08).

Non-EU User Behavior on EU vs. Non-EU Websites

A spillover effect would be evident if there were no differences in the behavior of non-EU users on EU websites (Cell 2) and non-EU websites (Cell 4). This robustness check compares the average weekly visits between these groups.

Table W 6 shows that non-EU users visit EU websites (where the GDPR applies) less post-GDPR than pre-GDPR, but non-EU websites (where the GDPR does not apply) more post-GDPR. This result indicates a difference in behavior, suggesting that any spillover effect is limited.

EU vs Non-EU Users on Non-EU Websites

Similarly, we compare EU users (Cell 3) and non-EU users (Cell 4) on non-EU websites. Table W 7 reveals that EU users visit non-EU websites less post-GDPR, while non-EU users visit them more. This finding further suggests that the GDPR's impact is more pronounced on treated users and websites, and any spillover to non-EU users is minimal.

Website Location	User Location	Pre-/Post- GDPR	Average visits per week	Difference	Difference-in- Difference
EU		Pre-GDPR	3,159,196	-321,937	
websites	Non-EU	Post-GDPR	2,837,259	521,957	-555,844
Non-EU	users	Pre-GDPR	2,190,523	+233,907	555,011
websites		Post-GDPR	2,424,430	. 233,907	

 Table W 6:
 Comparison of EU- and Non-EU Visits for Non-EU Users (Cell 2 vs. Cell 4)

Table W 7: Comparison of EU- and Non-EU User Visits for Non-EU Websites (Cell 3 vs. Cell 4)

Website Location	User Location	Pre-/Post- GDPR	Average visits per week	Difference	Difference-in- Difference
	FIL	Pre-GDPR	1,578,877	-11,328	
Non-EU	EU users	Post-GDPR	1,567,548	-11,526	-245,235
websites Non-EU users	Non-EU	Pre-GDPR	2,190,523	+233.907	210,200
	users	Post-GDPR	2,424,430	. 233,907	

User Interface Changes Post-GDPR

To further examine potential spillover effects, we manually review the user interfaces of a random sample of 85 control websites using the Internet Archive's Wayback Machine. Accessing snapshots from the GDPR enactment date (May 25, 2018) and the last day of our observation period (November 30, 2019), we find:

- 94.12% of the control websites did not adjust their user interfaces regarding privacy levels post-GDPR.
- 5.88% made slight adjustments, but these changes did not fully comply with GDPR.

This finding suggests minimal voluntary compliance among non-EU websites for non-EU users, indicating a limited spillover effect.

Assessment of Strategic Geographic Shifts

There is a possibility that EU-based websites shifted their data processing locations to non-EU regions to avoid GDPR compliance for non-EU users, potentially contaminating our control group. To assess this, we create a stricter control group by including only websites with domain suffixes indicating a non-EU location (e.g., ".com").

We compare GDPR's effect on weekly visits between this stricter control group and our original control group:

- Short-term effect (3 months post-GDPR): No significant difference (stricter control group: -4.56%; original control group: -7.64%; p < 0.05).
- Long-term effect (18 months post-GDPR): No significant difference (stricter control group: -19.90%; original control group: -18.64%; p < 0.05).

This finding indicates that strategic geographic shifts are unlikely to have influenced our results.

Our robustness checks suggest that while a spillover effect of the GDPR to our control group may exist, its magnitude is limited and diminishes over time. The evidence supports the validity of our control group, and we conclude that our main findings regarding the GDPR's impact are robust. The GDPR may have introduced measurement error in our data if SimilarWeb's recorded user behavior does not match actual behavior post-GDPR due to users not consenting to tracking. An increased share of non-consenting users could widen the gap between actual and recorded user behavior.

We first conceptually argue that any measurement error in SimilarWeb data due to nonconsenting users is relatively small. We then validate this through an empirical study using "ground truth" data from another provider, AGOF. We find that GDPR's effect measured by SimilarWeb data is consistent with that measured by AGOF data. We conclude that any measurement error in SimilarWeb data is negligible and does not bias our results, allowing us to assess GDPR's effect on online user behavior accurately.

Conceptual Discussion of the Size of Measurement Error in SimilarWeb Data

Description of SimilarWeb and Available Data. SimilarWeb (www.similarweb.com) is our primary data source. Listed on the NYSE since May 2021 with a market capitalization of \$775 million as of November 8, 2024, SimilarWeb provides standardized measures of user behavior across our sample of 6,286 websites spanning 24 industries. It offers online usage metrics summarized in Table 3 of the main manuscript.

Description of SimilarWeb Data Collection and Analysis Methodology. SimilarWeb outlines its data collection and analysis methodology on its website SEC filings.⁹ It combines data from various sources¹⁰:

- 1. **Direct measurement**: Publishers share first-party analytics data (e.g., from Google Analytics) with SimilarWeb.
- 2. **Contributory Network:** SimilarWeb's consumer products, such as its browser extension, aggregated anonymous device traffic data, forming a user panel tracked over time.
- 3. **Partnerships:** Data from global partners, including internet service providers (ISPs), measurement firms, and demand-side platforms (DSPs), provide "digital signals" about online behavior.

⁹ https://www.sec.gov/Archives/edgar/data/0001842731/000162828021007036/similarwebfx1.htm#i37d24ed3283c4c7cbe80209961813bf4 13

¹⁰ https://support.similarweb.com/hc/en-us/articles/360001631538-Similarweb-Data-Methodology

4. **Public Data Extraction**: SimilarWeb captures publicly available data from websites, apps, and census data to refine its estimations.

Data processing involves¹¹:

- 1. **Data Collection**: Constructing representative datasets across countries, industries, user groups, and devices.
- 2. Data Synthesis: Cleaning and preparing data for modeling.
- 3. **Data Modeling**: Using machine learning predictive models on normalized data to estimate online traffic accurately over time.
- 4. Data Delivery: Providing data through dashboards or APIs.

GDPR Compliance and Potential Measurement Error. We discuss how GDPR requirements apply to SimilarWeb and argue that any measurement error due to non-consenting users is relatively small.

- 1. Statement from SimilarWeb: SimilarWeb provided a written statement that "GDPR had no impact on SimilarWeb data."
- 2. Non-Personal Data Processing: SimilarWeb claim publicly on their website¹² and in their (legally binding) SEC filing¹³ to remove all personally identifiable information (PII) at the source, including sensitive data such as gender and data from minors.¹⁴ They state: "We do not need PII or personal data to deliver any of the data and insights made available in our platform or through our API. In addition, we do not collect IP data and no metric in our platform, including Unique Visits, requires or uses IP data." By not processing personal data, SimilarWeb positions itself outside the jurisdiction of GDPR, making it largely immune to measurement errors due to GDPR.
- 3. **Compliance with Privacy Laws:** SimilarWeb states it complies with all privacy laws, including GDPR and CCPA. Specifically, they:
 - Employ a multi-step verification process to ensure that the data collected is devoid of PII.
 - Share behavioral data anonymously and aggregate it at the site- and app-level, not the user-level.
 - Do not use data for advertising or targeting, and do not use cookies to collect behavioral data.

¹¹ https://support.similarweb.com/hc/en-us/articles/360001631538-Similarweb-Data-Methodology

¹² https://support.similarweb.com/hc/en-us/articles/360001631538-Similarweb-Data-Methodology

¹³ https://www.sec.gov/Archives/edgar/data/0001842731/000162828021007036/similarwebfx1.htm#i37d24ed3283c4c7cbe80209961813bf4_13

¹⁴ https://support.similarweb.com/hc/en-us/articles/360001253797-Website-Demographic-Data

- 4. Data From Publishers: SimilarWeb uses direct measurement data from publishers who may be subject to GDPR. However, web analytics tools like Google Analytics can operate using "cookieless tracking" or "measurement protocol", allowing data collection without cookies¹⁵. Further, SimilarWeb relies on consent from its data providers to obtain first-party data. If a user does not consent, SimilarWeb imputes these missing observations using multiple data sources.
- 5. Browser Extension Data: SimilarWeb collects data from its browser extension, which has been available since August 2017¹⁶. It has around 1 million users across browsers like Chrome, Edge, Firefox, and Opera. Users consent to share anonymized traffic data in exchange for website statistics. Given that the extension predates GDPR and provides user benefits, users are unlikely to revoke consent due to GDPR. The data from the extension alone likely suffices for our research.
- 6. **Data from Partnerships:** SimilarWeb uses data from partners who may be subject to GDPR, potentially introducing measurement error. We address this concern in our empirical comparison with AGOF data.
- Public Data Sources: SimilarWeb uses publicly available data, exempt from GDPR's restrictions under Recital 162 for statistical purposes, and thus not subject to measurement error due to GDPR.¹⁷
- 8. **Methodology Update:** SimilarWeb updated its methodology in July 2019 and retroactively adjusted past data. Our data uses this "new" methodology¹⁸ consistently across the study period, and the timing does not coincide with GDPR's enactment, so the effects do not interfere.

In summary, SimilarWeb claims to use non-personal, aggregate data, positioning it outside GDPR's scope. While it may rely on data sources potentially affected by non-consenting users, SimilarWeb asserts it accounts for any measurement errors. Although we cannot entirely verify these claims due to lack of access to raw data, the reasons above suggest that any measurement error is minimal. We compare SimilarWeb data with a reliable "ground truth" data source, AGOF, to substantiate this conclusion.

¹⁵ https://developers.google.com/analytics/devguides/collection/protocol/v1

¹⁶ We could trace the first historic version of the browser extension on the Google Chrome Web Store using the Wayback Machine:

http://web.archive.org/web/20170101000000*/https://chrome.google.com/webstore/detail/similarweb-traffic-rank-w/hoklmmgfnpapgjgcpechhaamimifchmp

¹⁷ https://gdpr-text.com/read/recital-162/

¹⁸ https://en.globes.co.il/en/article-SimilarWebs-controversial-route-to-wall-street- 1001376912

Empirical Comparison of SimilarWeb and "Ground Truth" Data from AGOF

To evaluate the validity of SimilarWeb data, we obtained additional data from the German Association of Online Research (AGOF, www.agof.de) for 72 websites for 2018. AGOF collects non-personal data by generating anonymous aggregate traffic statistics (e.g., page impressions) and personal data based on legitimate interest (e.g., unique users). Therefore, AGOF does not suffer from measurement error due to non-consenting users, representing the actual "ground truth" user behavior in Germany. Unfortunately, AGOF data is only available for Germany, so we cannot perform the same test for other countries.

Description of AGOF and AGOF Data. AGOF is a joint industry committee and registered association of the digital media and advertising industry in Germany, independent of individual market participants. AGOF aims to provide a census measure of German advertising-relevant online user behavior, using commonly defined measurement conventions that remained stable during our observation period.¹⁹

AGOF data fulfills several requirements:

- Provides data on coverage and audience composition for all relevant German websites and apps.
- Complies with quality criteria of empirical social research, such as validity, reliability, and representativeness.²⁰
- Certified by external bodies: the German Media Analysis Working Group (AGMA)²¹ and the German Audit Bureau of Circulation (IVW)²², members of the International Federation of Audit Bureaux of Certification (IFABC)²³.

AGOF provides:

- Weekly Page Impressions: Number of pages visited per week on a website by the entire user base, comparable to SimilarWeb's weekly page impressions.
- Monthly Unique Users: The number of unique users visiting a website per month. It is comparable to SimiliarWeb's monthly unique visitors.

¹⁹ https://www.agof.de/en/studien/daily-digital-facts/methode/

²⁰ https://www.agof.de/en/studien/daily-digital-facts/methode/

²¹ https://www.agma-mmc.de/

²² https://www.ivw.de/englische-version

²³ https://www.ifabc.org/members/full-member-list-alphabetically

AGOF measures page impressions anonymously, without relying on personal data. Thus, GDPR restrictions do not apply, allowing data collection without user consent.²⁴ AGOF relies on legitimate interest for measuring unique users to process the personal data necessary to identify users on repeated visits.

We compared AGOF with SimilarWeb data to assess the validity of SimilarWeb data based on 72 websites included in both data sets. The website-instances from SimilarWeb included in this analysis only track German user behavior, but AGOF tracks global user behavior. Thus, we expected larger differences for websites with a larger share of international traffic. Therefore, we reduced the websites in our comparison sample to those 65 websites with a German traffic share larger than 80%. We obtained the German traffic share in April 2022 from SimilarWeb.

Description of AGOF Data Collection and Analysis Methodology. AGOF obtains its data from three sources:

- 1. **Technical Traffic Measurement:** AGOF and their technology provider INFOnline measure all page impressions of participating websites and apps, capturing unique clients (devices).
- 2. **On-Site and In-App Surveys**: Used to generate information on the audience (unique users) behind the browsers and clients.
- 3. **Telephone Survey**: A large, representative survey to determine the proportion of the internet audience relative to the entire population, used to extrapolate unique users from technical clients.

AGOF builds a virtual panel of about 300,000 participants, with the structure corresponding to population parameters from the telephone survey. The panel accounts for phenomena like cookie deletion.

Validation of AGOF Methodology. We investigated whether GDPR affected AGOF data:

- 1. **Statement from AGOF:** AGOF and INFOnline stated that GDPR did not lead to changes in their data collection. The collection relies on "legitimate interest" under Article 6(1)(f) of GDPR for processing personal data necessary for measuring unique users.
- Legal Basis Verification: We manually checked the legal basis used by the websites in our AGOF data using the Consent Management Platform (CMP) validator tool developed by IAB Europe.²⁵ INFOnline always uses legitimate interest as the legal basis to measure unique users, and users hardly ever opt-out (Johnson, Shriver, Du 2020).

²⁴ https://docs.infonline.de/infonline-measurement/en/gettingstarted/verfahrensbeschreibung/?h=anonymous#anonymous-measurement-methods

²⁵ https://iabeurope.eu/tcf-for-cmps/

In sum, relying on the AGOF data for our study comes with the advantage of AGOF data being measured based on non-personal data (in the case of page impressions) and legitimate interest (for unique users), which does not require a user's consent to process a user's personal data. Under legitimate interest, a user defaults to tracking, rendering AGOF data largely immune to measurement error from non-consenting users. Users can always delete their cookies or opt-out of cookies to prevent tracking. However, this option was already available long before GDPR and affects all online measurement tools. Interestingly, hardly any users opt-out. Johnson, Shriver, Du (2020), for example, find opt-out rates for targeted advertising on average to be as low as 0.23% of all ad impressions, with similar figures in the US (0.227%) and Europe (0.257%). Such cookie deletion would only affect the measurement of unique users, not other metrics, such as page impressions, visits, or the time spent on a website.

Comparison between AGOF and SimilarWeb Data. We conducted three tests to compare the two data sources pre- and post-GDPR:

- Raw Data Comparison: We compared the correlation and differences between page impressions and unique visitors in AGOF and SimilarWeb data before and after GDPR. We observed no significant differences, indicating that SimilarWeb data did not differ from AGOF data due to GDPR.
- Before-After Analysis: We used regression analysis without a control group (since AGOF only includes German websites) to examine the effect of the "Postperiod" dummy. The post-period effects were very close for both data sources for page impressions (aggregate analysis: -4.90% AGOF vs. -6.10% SimilarWeb) and unique visitors (aggregate analysis: -2.20% AGOF vs. -1.50% SimilarWeb).
- 3. GDPR Effect Estimation Using GSC Estimator: We applied the Generalized Synthetic Control estimator to page impressions for both AGOF and SimilarWeb data from January to December 2018, obtaining 3-month and 6-month effects. We found no statistical difference in GDPR's effect between the two data sources for page impressions 3 months post-GDPR (AGOF: -3.47% vs. SimilarWeb: -1.30%) or 6 months post-GDPR (AGOF: -1.99% vs. SimilarWeb: -1.03%). We could not repeat this analysis for unique visitors due to insufficient pre-treatment observations.

In summary, the tests indicate that SimilarWeb data aligns closely with AGOF data (unaffected by GDPR)), suggesting that SimilarWeb data is not significantly affected by measurement error due to GDPR.

Summary and Conclusion

Through conceptual discussion and empirical comparison with AGOF data, we demonstrate that SimilarWeb data does not suffer significantly from measurement error due to non-consenting users post-GDPR. SimilarWeb is a widely audited, industry-standard source of online user behavior information used by firms like Adobe, Google, The Economist, and researchers (e.g., Calzada and Gil, 2020; Lu et al., 2020).

Other scholars have relied on SimilarWeb data for GDPR-related studies. For instance, Congiu et al. (2022) used SimilarWeb data to study GDPR's effect on online user behavior. They concluded that the data fit their purpose and is unlikely to suffer from recording bias. Peukert et al. (2022, Appendix A2.2., pages 4-5) and Lefrere et al. (2024) also used similar data to study GDPR's impact on web technology providers and content provision.

Therefore, we are confident that SimilarWeb data serves our purpose of measuring the effect of GDPR on online user behavior accurately.

WEB APPENDIX G: ROBUSTNESS CHECKS CONCERNING CONFOUNDING FACTORS

Our calculation of GDPR's effect on online user behavior assumes no other significant confounding factors coincided with its enactment. Substantial changes affecting only the traffic of non-EU users on non-EU websites—but not EU users or non-EU users visiting EU websites—could influence the validity of our results. Therefore, we investigated whether other factors changed significantly for non-EU and EU users during the study period.

Specifically, we examined observable changes between the control and treatment website instances unrelated to the GDPR. We analyzed four potential confounding factors that might affect browsing behavior:

- Mobile Internet Speed
- Internet Access Share
- Laptop Usage Share
- Smartphone Usage Share

For example, higher internet speeds can lead to more browsing and increased access to devices or the internet can affect the number of online users.

Since examining changes per website instance is challenging, we focused on changes by user location. We used German users as a proxy for EU users and U.S. users for non-EU users. While this does not account for GDPR's effect on non-EU users visiting EU websites, it is a proxy to detect changes between the two groups.

As shown in Table W 8, we observed no substantial differences between non-EU and EU users in the pre- and post-GDPR comparison for these factors. The selected factors suggested that EU users might have exhibited increased web browsing behavior compared to U.S. users. Therefore, this robustness check indicates that these potential confounding factors did not negatively affect user behavior or undermine the validity of our results.

This analysis supports the assumption that other confounding factors did not coincide with GDPR's enactment in a way that would bias our results. The consistency in these factors between EU and non-EU users reinforces the validity of our findings on GDPR's effect on online user behavior.

Confounding Factor	User Group	Pre-GDPR:	Post-GDPR:
		January 2018	January 2019
Average Mobile Internet Connection	EU (Germany)	26.43 Mbps	31.69 Mbps (+ 20% YoY-Growth)
Speed	Non-EU (USA)	27.22 Mbps	32.01 Mbps (+ 18% YoY-Growth)
Share of Population with Access to the	EU (Germany)	91%	96% (+ 5.49% YoY-Growth)
Internet	Non-EU (USA)	88%	95% (+7 .95% YoY-Growth)
Share of Population Using Laptops or	EU (Germany)	76%	76% (+ 0.00% YoY-Growth)
Desktop	Non-EU (USA)	77%	77% (+ 0.00% YoY-Growth)
Share of Population Using Smartphones	EU (Germany)	75%	75% (+ 0.00% YoY-Growth)
8 r	Non-EU (USA)	78%	78% (+ 0.00% YoY-Growth)

Table W 8: User Group Comparison of Confounding Factors

Source: Datareportal Reports – Digital 2018 and Digital 2019

WEB APPENDIX H: ROBUSTNESS CHECKS CONCERNING THE SYNTHETIC CONTROL METHOD

In calculating GDPR's effect, we made several methodological decisions that could potentially impact our results, including the choice of estimator, criteria for matching control and treatment websites, and the number of control websites used. We conducted several sensitivity analyses to assess the robustness of our findings to these decisions.

We employed the Generalized Synthetic Control (GSC) estimator (Xu 2017), implemented in the R package gsynth, to calculate GDPR's effect on online user behavior. The GSC estimator extends the synthetic control method (Abadie and Gardeazabal 2003; Abadie et al. 2010, 2011, 2014) by unifying it with linear fixed-effects models (Bai 2009; Pang 2010, 2014; Gobillon and Magnac 2016) under a general framework where difference-in-differences (DID) is a special case.

The GSC estimator offers advantages such as handling multiple treatment units or variable treatment periods (although these advantages do not play a role in our case) and providing readily interpretable uncertainty estimates (though we do not report them here). It includes safeguards against serial correlation by using a parametric bootstrap procedure that resamples residuals conditional on observed covariates and unobserved factors (Xu 2017, p. 65), preserving serial correlation within units and avoiding underestimating standard errors.

However, different methods and choices might yield varying results. Specifically, we made two key decisions:

- Limiting the number of control websites to five to avoid overfitting.
- Requiring control websites to belong to the same industry as the treatment website.

To examine the influence of these decisions, we conducted four robustness checks:

- 1. Using an Alternative Synthetic Control Estimator
- 2. Relaxing the Industry Specification for Control Websites
- 3. Matching Control Websites Based on EU Traffic Share
- 4. Increasing the Number of Control Websites

Usage of Another Synthetic Control Estimator

Our analysis applies the GSC estimator implemented in the "gsynth" package in R, a popular R package and method for synthetic control. In this first robustness check, we examine whether using the original synthetic control estimator results in similar GDPR effects. More specifically, we compare the results obtained using the "gsynth" package to another popular synthetic control

estimator package: the "synth" package. We calculate GDPR's short- and long-term effects on our main metric for a random subsample of 3,455 website-instances. We find no significant difference between the results of the "gsynth" and the "synth" packages for the short-term effects (average effect for "synth": -4.96%; average effect for "gsynth": -6.88%; no significant difference on 5%-level) or the long-term effects of GDPR (average effect for "synth": -18.39%; average effect for "gsynth": -19.29%; no significant difference on 5%-level).

Calculation of Synthetic Control Group without Industry Specification

We next examine whether requiring control websites to belong to the same industry as the treatment website affects our results. Thus, we remove this requirement and calculate the correlation of all possible control website-instances with the treatment website-instance. The GSC estimator thus includes the five control website-instances with the highest correlation with the treatment website-instance irrespectively of the websites' industry. We then calculate GDPR's short- and long-term effects for a random subset of 100 treatment website-instances. This robustness check shows that not requiring the control website-instances belong to the same industry as the treatment website-instance results in no significant difference in the short-term effects (average effect for new specification: -2.84%; average effect for original specification: -6.69%; no significant difference on 5%-level) or the long-term effects of GDPR (average effect for new specification: -5.65%; average effect for original specification: -5.65%; av

Calculation of Synthetic Control Group with EU Traffic Share as Matching Variable

As we discussed in the prior section, in which we examined the validity of our control group, websites with a similar share of EU traffic might have a similar incentive to comply with GDPR. Thus, to account for this potential alignment of a website's propensity to comply with GDPR and its EU traffic share, we conduct the following robustness check: Instead of limiting the potential pool of control website-instances to the ones within the same industry as the treatment website-instance, we require the potential control website-instances to be part of a website with a treated website-instance with the same or similar EU share as the focal treatment website-instance.

We then use a random subsample of 393 websites to re-calculate GDPR's short- and long-term effects for our main metric, the weekly visits.

The results of this robustness check show no significant difference in either the short-term effects (average effect for new specification: -7.07%; average effect for original specification: -3.79%; no significant difference on 5%-level) or the long-term effects of GDPR (average effect for new

specification: -4.21%; average effect for original specification: -5.77%; no significant difference at 5%-level).

Calculation of Synthetic Control Group with a Higher Number of Control Websites

To avoid overfitting, we limit the number of control website-instances for the GSC estimator to the five website-instances that have the highest pre-treatment correlation with our treatment website-instance. This robustness check examines whether our estimates are robust to an increase in the number of control website-instances selected for the GSC estimator. Thus, we select ten instead of five control website-instances with the highest pre-treatment correlation for a subsample of 60 treatment website-instances. We then re-calculate GDPR's short- and long-term effects for our main metric, the weekly visits. The results are similar to our main study's results, i.e., we find no significant difference in either the findings for the short-term (average effect for 10 control websites: -13.91%; average effect for 5 control websites: -12.62%; no significant difference on 5%-level) or the long-term effects of GDPR (average effect for 10 control websites: -17.36%; average effect for 5 control websites: -12.62%; no significant difference on 5%-level).

WEB APPENDIX I: ROBUSTNESS CHECK CONCERNING THE CHOICE OF THE ESTIMATOR

To measure GDPR's effect on online usage behavior, we use the generalized synthetic control (GSC) estimator in Equation (1) as our main specification in the paper. For robustness, we present the results of a difference-in-differences (DID) estimator.

We use a sub-sample to determine DID estimates for our main usage behavior metric q, the weekly visits. The sub-sample is smaller (1,104 websites) because it requires that treatment and control website-instances belong to the same website. Specifically, we assign non-EU website-instances with EU users to the treatment group (see Figure 1, Cell 3) and non-EU website-instances without EU users to the control group (see Figure 1, Cell 4). In Figure 3, we plot the average log(visits + 1) for the treatment and control group, which confirms similar trends pre-GDPR for the websites in the treatment and the control group, but diverging trends post-GDPR. Our DID analysis requires parallel trends on weekly visits as an identifying assumption.

Using the regression model (W15) below and the described treatment and control group assignment, we calculate the treatment effect ($\beta_{3,q,wi}$) for the weekly visits of every website-instance *wi*. To determine the development of the treatment effect over time (here measured in weeks), we rerun our analysis several times, extending the duration of the post-GDPR's enactment period in each analysis. We first consider a post-treatment period of 3 months post-GDPR's enactment (up to August 25th, 2018, thus including observations from week 1 to week 60), then periods of 6 (week 1 to 73), 9 (week 1 to 86), 12 (week 1 to 99) and 18 (week 1 to 125) months. These analyses enable us to determine GDPR's short-term effect (i.e., 3 months post-GDPR's enactment) and long-term effect (i.e., up to 18 months post-GDPR's enactment).

We report the results of our DID analysis in Table W 9. When comparing the DID estimates (Table W 21) with our GSC estimates (Table 5), we find slightly but consistently larger estimates for the DID estimator of GDPR's short-term effect on visits (3 months post-GDPR's enactment; on average, DID: -7.18% versus GSC: -4.88%; median DID: -11.02% versus GSC: -3.49%), and GDPR's long-term effect on visits (18 months post-GDPR's enactment; on average, DID: -12.50% versus GSC: -10.02%; median DID: -14.67% versus GSC: -8.91%). Our results for weekly visits resemble the results of Goldberg et al. (2022), who found an 8.09% drop in recorded page views and a 5.59% drop in recorded revenue 4 months post-GDPR in a DID analysis using the users from North America as a control group.

(W16) $ln(Y_{q,t,r})$	$w_{i} + 1) = \beta_{0,q,w_{i}} + \beta_{1,q,w_{i}} * EU_{w_{i}} + \beta_{2,q,w_{i}} * Postperiod_{t} + \beta_{3,q,w_{i}} * Treated_{t,w_{i}} + \epsilon_{q,t,w_{i}}$
$Y_{q,t,wi}$:	Value of usage behavior metric q in week t on website-instance wi
EU_{wi} :	EU-Dummy, i.e., binary variable for which a value of 1 indicates that the users or website of website-instance <i>wi</i> are EU-based, else 0
Postperiod _i :	Post-period-Dummy, i.e., binary variable for which a value of 1 indicates that the observation in week t lies in the post-treatment period, else 0
Treated _{t,wi} :	= EU_{wi} * Postperiod _t ; Treatment-Dummy, i.e., binary variable for which a value of 1

indicates that in week t, website-instance wi needs to consider GDPR, otherwise 0

 $\epsilon_{q,t,wi}$: Error term for usage behavior metric q in week t for website-instance wi

These slightly higher estimates indicate a limited spillover effect of GDPR on non-EU websiteinstances. As we outline in the main manuscript, this control group may be contaminated as those non-EU websites with EU users (and belonging to the treatment group) and non-EU users (belonging to the control group) may decide to adopt GDPR for the entire website, thus all users, e.g., to avoid potentially costly differential treatment of EU and non-EU users on the same website. Thus, in the presence of such a spillover effect, any specification with non-EU website-instances as the control group may understate GDPR's effect. In other words, in the case of a strong spillover effect, we would expect the treatment and control traffic to be more similar post-GDPR's enactment (see also Figure 3) and expect to find a smaller GDPR effect as both treatment and control units would comply with GDPR and thus become more similar. Instead, we find consistently larger instead of smaller GDPR estimates, supporting the suitability of our control group.

Using the subsample of our data with non-EU website-instances with and without EU traffic in our DID analysis allows us to observe a direct control group for each treatment website-instance. Unfortunately, such a direct control group is unavailable for all treatment website-instances, so we cannot provide DID estimates for our entire sample of treatment website-instances. Therefore, we use the GSC estimator as the main specification in our manuscript and construct a synthetic control group for each treatment website-instance. As the control group used for the DID analysis constitutes a subset of the non-EU website-instances in our sample, we cannot rule out entirely that some website-instances in our control group complied with GDPR. Therefore, we conclude that although a spillover effect of GDPR on our control group may be present, the size of such a spillover effect is limited, given our DID results.

Table W 9:Comparison of the Effect of GDPR on the Weekly Visits Obtained from a Difference-
in-Differences (DID) Estimator and a Generalized Synthetic Control (GSC)
Estimator

Metric		3 months	6 months	9 months	12 months	18 months
Visits (DID	Mean:	-7.18%	-10.58%	-11.41%	-12.03%	-12.50%
Estimator	Median:	-11.02%	-12.60%	-13.51%	-13.52%	-14.67%
	Number of treatment websites:	1,104	1,104	1,104	1,104	1,104
	Number of control websites:	1,104	1,104	1,104	1,104	1,104
Visits (GSC	Mean:	-4.88%	-7.22%	-9.07%	-9.57%	-10.02%
Estimator)	Median:	-3.49%	-5.54%	-7.54%	-8.24%	-8.91%
	Number of treatment websites:	5,683	5,683	5,683	5,683	5,683
	Number of control websites:	1,701	1,701	1,701	1,701	1,701
	p-value of t-test:	0.12	0.01**	0.08	0.06	0.06

Notes: Significance level: *** 0.1%-level ** 1%-level * 5%-level.

The table summarizes GDPR's effect on weekly visits obtained from a difference-in-differences (DID) estimator using non-EU website-instances with EU users as the treatment group and non-EU website-instances with non-EU users as the control group. The table shows the mean and median values of the change in visits due to GDPR across all websites. The table compares the DID results with our main results obtained from a generalized synthetic control (GSC) estimator, as shown in Table 5.

For example, the 3-month effect of GDPR for the weekly visits based on a difference-in-differences estimator across all websites (second-row / third column) is, on average, -7.18%, and the median effect is -11.02%. The number of treatment and control websites is 1,104.

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