The Impact of the EU's GDPR Announcement on US Tech Companies' Returns with European Exposure

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Abstract

This study investigates the impact of the European Union's General Data Protection Regulation (GDPR) announcement on April 27, 2016, on the stock returns of U.S. technology companies with varying levels of European exposure. Specifically, the analysis distinguishes between companies deriving more than 25% of their revenue from Europe (treatment group) and those with less than 25% (control group). A two-way fixed effects Difference-in-Differences (DiD) framework examines the relationship between the announcement and daily stock returns. The interaction term in the model captures the differential impact of the GDPR announcement on the stock returns of firms with significant European exposure compared to those with limited exposure. The robustness of the results is further validated through a Monte Carlo simulation, which randomly reassigns treatment across firms to generate a distribution of randomized effects. The data for this study was sourced from CRSP (Center for Research in Security Prices) for stock returns and Orbis for geographic revenue segmentation. The empirical findings reveal that the interaction term capturing the GDPR's announcement effect is statistically insignificant, indicating no substantial market response among the firms analyzed.

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Introduction

Context and regulation

In the digital era, personal data has become a critical economic resource. For technology companies, collecting and analyzing vast amounts of data enables service optimization, improved ad targeting, and enhanced customer experience (Solove, 2013). However, the growing reliance on data has sparked significant concerns over privacy and data security.

In response to these issues, the European Union adopted the GDPR, one of the most ambitious and stringent data protection regulations, aiming to safeguard citizens' rights in an increasingly connected environment (Regulation (EU) 2016/679, 2016). The GDPR represents a significant step forward in the EU's proactive approach to data protection, addressing pressing issues related to the handling of personal data by large tech companies. This regulation was adopted on April 27, 2016, and became enforceable, taking full effect on May 25, 2018.

Although it followed the GDPR's announcement in 2016, the 2018 Cambridge Analytica scandal highlighted the vulnerability and commercial value of personal data even further. It was revealed that Cambridge Analytica had improperly obtained data from millions of Facebook users to create detailed profiles for electoral manipulation purposes, influencing the 2016 U.S. presidential election Isaak & Hanna (2018). This scandal demonstrated how personal data could be exploited to influence political decisions on a large scale, reinforcing public and political opinion on the need for strict regulations on privacy management. This incident triggered a wave of criticism regarding data management by Big Tech and underscored the importance of introducing laws like the GDPR, which aim to curb abuses and ensure greater transparency. In fact, the GDPR imposes stringent consent and accountability requirements to prevent similar incidents in the future.

The main innovations introduced by the GDPR include the need to inform and obtain consent from individuals whose data is being processed; the obligation to ensure "Privacy by Design" and "Privacy by Default"; maintaining a record of processing activities; and reporting data breaches to supervisory authorities. For companies, penalties for violations of data protection can reach up to 4% of their worldwide annual revenue from the previous fiscal year.

In this context, the GDPR emerges as a forward-looking response to concerns already present across Europe, helping to protect citizens' rights in an age of increasing surveillance Zuboff (2019).

Studies such as Li et al. (2019) highlight the operational and strategic impacts of GDPR compliance, particularly for large technology companies reliant on data-driven business models. For these firms, the introduction of GDPR marked a shift in managing personal data, with substantial implications for compliance strategies and financial performance.

Impact of GDPR on American Tech Companies

The implementation of the GDPR in May 2018 marked a turning point in the regulation of privacy and personal data protection, presenting significant challenges for technology companies, particularly U.S.-based companies operating in Europe.

Leading companies, heavily reliant on data to optimize their business models, were compelled to comply with new regulations regarding the collection, processing, and storage of personal data. According to Li et al. (2019), the GDPR has impacted the business strategies of tech companies, requiring them to revise not only their IT infrastructures but also their internal privacy policies, significantly increasing compliance costs.

The GDPR has necessitated a paradigm shift in how companies manage personal data, compelling them to prioritize robust legal and technical frameworks to ensure compliance. These regulatory demands have fundamentally reshaped operational practices, driving organizations to adopt comprehensive measures for safeguarding data and embedding privacy considerations into their systems from the outset. The significant financial and reputational risks associated with non-compliance—such as fines or loss of consumer trust—have further motivated businesses to invest heavily in creating and maintaining infrastructures that meet the regulation's high standards. This has led to significant changes in their strategic and operational priorities.

A notable example of the financial repercussions of GDPR non-compliance is the €1.2 billion fine imposed on Meta (Facebook) in 2023 for unlawful data transfers to the United States. The European Data Protection Board (EDPB) determined that Meta's practices violated the GDPR by failing to protect personal data adequately during these transfers, which exposed users to privacy risks. This record-breaking fine underscore the severe financial implications companies can face for non-compliance and highlights the importance of ensuring robust data protection frameworks, especially for multinational technology firms European Data Protection Board (2023).

A critical aspect has been the impact on the business models of tech companies. The regulation has limited the freedom with which companies can collect and use user data, affecting personalization and targeted advertising, which are central to many of these enterprises. This shift has had direct implications for data monetization, reducing the ability to generate profits through targeted advertising key aspect for giants like Facebook and Google, and also other major companies. According to Li et al. (2019), these restrictions have led to a strategic realignment for many companies, forcing them to explore new revenue models and adapt their service offerings.

The GDPR has also impacted corporate reputation. Privacy violations or the perception of non-compliance with regulations can have devastating consequences, not only legally and financially but also in terms of user and investor trust. Linden et al. (2020) highlight how companies have been prompted to improve the transparency of their privacy policies to prevent damage to their public image.

Furthermore, the GDPR has generated significant uncertainty by imposing a new regulatory framework not only across Europe but with global implications. U.S.-based tech companies, which already operate in diverse regulatory contexts, have faced the challenge of navigating a complex regulation, with the risk of unintentional violations. This has influenced their strategic decisions, leading to a renewed focus on regulatory compliance. Large American tech companies with significant exposure to European markets have had to adapt their data management practices, facing evolving costs and strategic implications Li et al. (2019).

Research Question and Hypotheses

This study aims to evaluate the economic impact of the GDPR's announcement on the financial performance of American technology companies. Specifically, it investigates the stock market reaction to the GDPR by analyzing whether the adoption led to differential changes in stock returns between companies with substantial European exposure and those with minimal or no European exposure. The research addresses the following question: What is the effect of the GDPR's announcement on the stock returns of American technology companies with significant European presence compared to those without such presence?

To explore this, the study examines whether the anticipation of regulatory compliance costs, operational challenges, and strategic adjustments associated with the GDPR announcement created observable disparities in market performance between these two groups of companies. The hypotheses are formulated as follows:

H_0 (Null hypothesis): The GDPR's announcement had no significant effect on the stock returns of American tech companies with substantial European exposure compared to those with minimal exposure.

H_A (Alternative hypothesis): The GDPR's announcement had a significant effect on the stock returns of American tech companies with substantial European exposure compared to those with minimal exposure.

Literature Review

The implementation of the General Data Protection Regulation (GDPR) has generated extensive academic discussion regarding its impact on financial markets and economic implications particularly for firms operating within or exposed to the European Union. This literature review evaluates existing research to understand the regulatory, market, and economic effects of GDPR, with a focus on its influence on the stock performance and financial operations of American technology companies. The articles reviewed have been particularly useful in shaping our understanding of these impacts, providing both theoretical foundations and empirical insights critical to our analysis. The first section explores the foundational methodologies underpinning our approach, focusing on seminal works in event-study analysis.

Foundational studies

Fama et al. (1969) pioneered the event study methodology, which is used to evaluate the efficiency with which stock prices incorporate new information. In examining stock splits as a case in point, the authors demonstrated that abnormal returns could be quantified by comparing actual stock performance with expected returns, which were calculated through a market model. The results demonstrated that stock prices adjust rapidly to public announcements, providing empirical support for the Efficient Market Hypothesis (EMH).

This foundational work is highly relevant to our project, as it establishes a methodological and theoretical basis for studying market reactions to announcements of the kind made in connection with the GDPR. Although Fama et al. do not explicitly employ the term 'cumulative abnormal returns' (CARs) in the manner that it is currently defined, their approach to measuring abnormal returns over an event window is consistent with the methodologies used in the estimation of CARs. Similarly, while they do not utilize the technique of difference-in-differences (DiD), their work emphasizes the importance of isolating the effect of specific events on stock performance, which informs our use of DiD to capture broader, long-term market impacts.

MacKinlay (1997) provides a detailed framework for using event studies to assess how specific events impact asset prices. By outlining statistical techniques for estimating normal and abnormal returns, the paper highlights the methodology's ability to evaluate market reactions to new information, including regulatory changes. This article supports our report by providing tools to analyze stock market responses to GDPR announcements. MacKinlay’s focus on abnormal returns aligns with our analysis of American tech firms with European exposure, complementing our use of DiD for longer-term impacts.

GDPR and Markets

One key area of research examines the stock market reactions to the GDPR. This section explores studies that analyze how market participants perceive and react to the implementation of data protection regulations, particularly in the context of firms with significant European exposure.

Arcuri (2020) examines the impact of the GDPR on the stock prices of European financial institutions. The study compares the stock market performance of these institutions before and after the GDPR's implementation, highlighting the regulation's impact on financial market dynamics. The findings indicate a generally positive market response, indicating that investors viewed the GDPR as a strategic regulatory advancement that could enhance trust, compliance, and competitive advantage rather than solely as a compliance burden. However, the results are not uniform across all contexts. Variations in the stock market's reaction across different European countries underscore the importance of local institutional frameworks, economic conditions, and sectoral resilience in shaping perceptions of regulatory impact.

This study is highly relevant to our report, which examines the economic impact of GDPR’s announcement on the financial performance of American technology companies. The author focuses on European financial institutions and GDPR implementation. Our research, however, focuses on the announcement phase, assessing whether it caused disparities in stock returns between U.S. tech firms with different levels of European exposure.

GDPR and Operational implications

Shifting from stock market analyses, this section focuses on the broader economic and industry-specific impacts of GDPR, particularly its compliance costs and sector-specific challenges. It examines how the regulation has shaped financial burdens and operational strategies, emphasizing the unique effects on data-driven industries such as technology firms with significant European exposure.

Frey and Presidente (2024) explore the economic consequences of the (GDPR) on firm performance, providing valuable insights into the costs and implications of privacy regulation. Utilizing a Two Way Fixed Effects methodology, the authors examine how GDPR implementation influenced firms’ profits, sales, and operational adjustments across 61 countries. Their findings reveal that firms with significant exposure to European markets experienced an average 8% decline in profits and a 2% drop in sales, driven largely by the compliance costs and operational restructuring required to meet GDPR’s stringent data privacy standards. The study shows smaller firms faced greater financial strain than larger ones, while data-intensive industries like technology and advertising were most affected. It also highlights GDPR’s extraterritorial impact on non-EU firms with strong European ties. This work is directly relevant to our project as it offers a comprehensive analysis of GDPR’s global economic implications, particularly its differential effects across firms based on size, industry, and geographic exposure. These insights provide a foundation for understanding how regulatory burdens influence firm performance and investor expectations.

Commission Nationale de l'Informatique et des Libertés (2024) provides a detailed examination of the broader economic implications of GDPR, focusing on compliance costs and operational adjustments faced by businesses both within and outside the European Union. The report highlights how GDPR, while successful in strengthening data protection and consumer trust, has also imposed significant financial and operational challenges, particularly for small and medium-sized enterprises (SMEs). Larger firms, with greater resources, were better equipped to absorb these costs, creating differential effects across firm sizes. The study underscores the regulation’s extraterritorial reach, as firms outside the EU with European market ties also faced substantial compliance demands.

McKinsey & Company. (2017) examines the financial and operational challenges businesses face in preparing for GDPR compliance. The study finds that GDPR compliance efforts could increase operational costs by as much as 70 to 80 percent, creating significant financial burdens, particularly for firms heavily reliant on European markets. Despite these challenges, the report emphasizes that strategic, targeted compliance approaches can mitigate unnecessary costs and even position firms to leverage GDPR as a foundation for competitive advantage in digital transformation.

This paper supports our project by linking GDPR compliance costs and operational adjustments to investor expectations. For U.S. tech firms with European exposure, these burdens likely influenced market reactions and stock valuations. McKinsey’s insights on uneven compliance costs align with our focus on stock market disparities, providing a framework to connect regulatory demands to stock performance and broader market dynamics.

Data and Sample Selection

The selection of data for this study was guided by the desire to assess the impact of GDPR on the publicly traded U.S. tech companies. For this study, financial data was sourced from two primary databases: Orbis and the Center for Research in Security Prices (CRSP). Orbis provided detailed company-level financial information, including geographic revenue segmentation, while CRSP supplied stock returns. These datasets were selected for their comprehensiveness, accuracy, and relevance to financial research.

Orbis

To study the effects of the GDPR on the stock returns of European tech companies, we extracted fiscal data for the year 2015 of large U.S.-based tech firms. The data was sourced from the Orbis database, a comprehensive global financial database widely used for financial and economic research. Orbis was selected due to its extensive coverage of public companies, detailed financial metrics, and reliable information on geographic revenue breakdowns, which are critical for assessing European exposure. Focusing on publicly listed U.S. companies categorized under SIC code 737, this classification covers industries such as computer programming, data processing, and other computer-related services sectors that are likely to be directly affected by GDPR regulations due to their heavy reliance on data processing and management. To have a flexible approach that allows a broader view, we decided to classify a company as "very large" if it met at least one of the following criteria:

• Operating Revenue: Companies with an annual revenue of at least $130 million were included to ensure the sample consisted of companies with a notable market presence.

• Total Assets: Companies with at least $260 million in total assets were selected to ensure financial robustness, an important consideration given the compliance costs associated with GDPR.

• Employees: A minimum threshold of 1,000 employees was used to focus on larger enterprises, as they are more likely to have structured compliance capabilities.

After applying the filters, we identified a total of 630 technology companies from Orbis that met at least one of the initial specifications. However, upon further examination of the geographical revenue segmentation data, we found that only 68 of these companies had the necessary detailed information available. Many firms were excluded because their revenue data lacked the granularity needed to precisely determine the geographic regions where revenues were generated. While this limitation significantly reduced the sample size, it ensured that the remaining companies provided the detailed and reliable data necessary for robust analysis. To assess the differential impact of GDPR based on European revenue exposure, the companies were divided into two groups:

• Treatment Group: Companies where more than 25% of total revenue comes from European operations. These firms are expected to be more directly affected by GDPR requirements, potentially influencing their stock returns due to compliance costs, operational changes, or shifts in investor perception. This group is composed of 35 companies.

• Control Group: Companies where less than 25% of total revenue comes from Europe. These companies, while part of the tech sector, likely face less direct impact from GDPR, serving as a comparative baseline for understanding broader market trends. This group is composed of 33 companies.

This dataset provides a structured basis for analyzing whether the introduction of GDPR had a measurable impact on the stock returns of tech companies with high versus lower European revenue exposure. By focusing on large, publicly traded firms, this analysis aims to yield insights into how regulatory changes in data protection influence financial performance in the tech sector. There are various limitations and assumptions to consider to correctly understand the results of our research. By focusing on large public companies, we may not fully capture the GDPR's impact on smaller tech firms or private companies that could have less capacity to adapt to compliance costs. Consequently, the findings may primarily reflect the experiences of large, resource-rich companies.

Furthermore, selecting firms based on at least one of the criteria of $130 million in revenue, $260 million in assets, or 1,000 employees ensures the inclusion of substantial, established enterprises. This focus intends to examine firms with the resources and stability to respond effectively to GDPR, but it may skew results towards companies with significant compliance resources. For simplicity, we've grouped all sales listed under "Europe," "EU," or "EMEA" as "European sales." This categorization may introduce a bias, as it potentially includes revenue from regions with varying degrees of GDPR relevance, which could influence the results.

CRSP

In addition to the Orbis database, our analysis utilized data from the Center for Research in Security Prices (CRSP), accessed via the Wharton Research Data Services (WRDS) platform. CRSP is renowned for its comprehensive and accurate financial data on stock prices, returns, and trading volumes for securities listed on NYSE, AMEX, and NASDAQ. This database provides essential datasets for financial research, including stock indices, portfolios, bond prices, treasury yields, and mutual fund performance metrics.

A key advantage of CRSP is its use of unique permanent identifiers for securities, allowing consistent tracking despite ticker changes, mergers, or delistings. This feature is particularly crucial for longitudinal studies, such as event studies or performance analyses. Additionally, CRSP ensures reliability by accurately adjusting for dividends, stock splits, and other corporate actions.

The WRDS platform, developed by the Wharton School of the University of Pennsylvania, offers a robust interface for accessing and analyzing these datasets. Its standardized processes and sophisticated tools facilitate efficient data extraction and analysis, which is critical for academic and professional research.

For this analysis, the primary variable of interest was the RET variable from CRSP, representing the Holding Period Return. This variable is adjusted for dividends and corporate actions, providing a comprehensive view of stock performance. We focused on daily stock return data spanning from January 1, 2016, to May 1, 2017, capturing both the pre-GDPR and post-GDPR periods.

The exact date of April 27, 2016, marking the official adoption of GDPR, was designated as t=1 and all periods after. Stock returns were analyzed for the period leading up to and following this date, adjusted for dividends and corporate actions using the RET variable. This approach ensures an accurate representation of total returns, which is crucial for evaluating how stock performance evolved in response to GDPR. By focusing on this timeline, we attempt to capture market reactions to the adoption of the regulation.

Descriptive statistics

This section examines the financial and operational characteristics of the Treatment (35 companies) and Control (33 companies) groups, emphasizing their differences and shared features. These two subgroups were defined based on the proportion of revenue derived from Europe/EMEA, with the Treatment group including firms where European revenue exceeds 25% of the total, and the Control group comprising those with less than 25%.

Control Group

Firms in the Control group are generally smaller in scale compared to those in the Treatment group. As shown in Table 1, the mean operating revenue for this group is $3.008 billion, with a standard deviation of $6.956 billion, reflecting variation in firm size. Employee numbers also expose some variety ranging from 413 to 221,700, with an average of 17,373. North American sales dominate their revenue composition, averaging $1.927 billion, while revenue from Europe/EMEA is significantly lower at $405 million. On average, only 14.1% of their total sales are derived from Europe/EMEA. This data aligns with the classification criteria for this group, where European exposure is limited.

CONTROL	Median	Mean	SD	Min	Max
Operating revenue (Turnover) (2015)	955,419	3,007,836	6,955,889	91,182	38,226,000
Number of employees (2015)	3,826	17,373	43,886	413	221,700
Total Sales	955,419	3,007,836	6,955,889	91,182	38,226,000
Sales in US/North America	657,085	1,927,218	3,630,292	86,106	17,325,000
Sales in Europe/EMEA	130,775	405,072	907,244	3,443	4,898,000
(Sales in Europe/EMEA) / (Total Sales)	0.1438	0.1412	0.0678	0.0218	0.2498

Note. All data in thousand USD, except for the last line. 33 companies considered.

Table 1: Descriptive Statistics for the Control Group

Treatment Group

Firms in the Treatment group operate at larger scale compared to those in the Control group. As indicated in Table 2, their mean operating revenue is $8.866 billion. Employee counts also demonstrate variability, ranging from 390 to 377,757, with a mean of 20,782. Sales from North America remain critical for these firms, averaging $4.188 billion. However, the defining feature of this group is its significantly higher reliance on European markets. Revenue from Europe/EMEA averages $3.651 billion, accounting for 36.7% of total sales on average. These statistics highlight the European reach of firms in this group compared to the more North American focused Control group.

TREATMENT	Median	Mean	SD	Min	Max
Operating revenue (Turnover) (2015)	942,753	8,865,996	23,515,410	51,049	93,580,000
Number of employees (2015)	3,333	20,782	65,857	390	377,757
Total Sales	942,753	8,865,996	23,515,410	51,049	93,580,000
Sales in US/North America	430,626	4,188,420	10,901,170	7,191	42,941,000
Sales in Europe/EMEA	289,975	3,651,434	10,269,527	12,940	50,639,000
(Sales in Europe/EMEA) / (Total Sales)	0.3389	0.3674	0.0985	0.2535	0.6800

Note. All data in thousand USD, except for the last line: Sales in Europe/EMEA/Total Sales. 35 companies considered.

Table 2: Descriptive Statistics for the Treatment Group

Treatment and Control Group Comparability

Despite these differences in the mean, the median values for revenues and employee counts between the two groups are more comparable. The median operating revenue for the Control group is $955,419 thousand, very close to the $942,753 thousand observed in the Treatment group. Similarly, the median number of employees is 3,826 for the Control group and 3,333 for the Treatment group. These similarities suggest that the two groups align more closely at the central tendency level once the influence of extreme values is mitigated. The differences in mean values are largely driven by extreme outliers, making them less representative of the typical firm in each group.

Stock Returns of the Control and Treatment Companies

The analysis of stock returns in Table 3 highlights similarities between the Treatment and Control groups, particularly in terms of their mean daily returns. The mean for the Control group is 0.000622, very close to the Treatment group's mean of 0.000695, suggesting comparable average stock performance across the two subgroups, despite the differences in geographic focus and operational scale.

In terms of variability, the standard deviation (SD) for the Treatment group is 0.023729, slightly higher than the Control group, consisting of 0.021501. However, when compared to their respective means, both groups show a relatively high degree of variability. The ratio of the SD to the mean (also known as the coefficient of variation, CV) is approximately 34.6 for the Control group and 34.1 for the Treatment group, indicating that the variability in stock returns is substantial relative to the average daily returns. This suggests that, while the mean values are similar, stock returns in both groups exhibit notable dispersion, which may reflect the sensitivity of these companies to even small fluctuations in financial markets or sector-specific dynamics.

Nonetheless, there is a notable difference between the medians of the returns for the treatment and control group, 0.000779 for control versus 0.000349 for treatment. This may be attributed to the geographic focus of the companies. Namely, the return of treatment companies could be slightly skewed due to the different regulatory or geopolitical factors they face due to having greater exposure to European markets.

Finally, the full dataset, combining both groups, reveals a median return of 0.000583, mean return of 0.000659, and SD of 0.022642. This consolidated view reinforces the overall comparability of stock return profiles across the two subgroups.

STOCK RETURNS	Median	Mean	SD	Min	Max
Control Group	0.000779	0.000622	0.021501	-0.460195	0.237162
Treatment Group	0.000349	0.000695	0.023729	-0.277425	0.262893
Full Dataset	0.000583	0.000659	0.022642	-0.460195	0.262893

Table 3: Descriptive Statistics for Stock Returns

In analyzing companies from 2016, we observed that some of them have changed their names or ticker symbols in subsequent years. Since our research focuses on a period before these changes, we retained the names and tickers relevant to the time under study to ensure consistency in the data. Specifically, we identified four cases: IAC/InterActiveCorp, listed as IACI in 2016 (currently IAC); Facebook, Inc., listed as FB in 2016 (now Meta Platforms, Inc. with ticker META); Fiserv, Inc., listed as FISV in 2016 (now trading as FI); and VASCO Data Security International, Inc., listed as VDSI in 2016 (currently known as OneSpan Inc. with ticker OSPN). These adjustments in naming conventions do not affect our analysis, as we rely on the identifiers valid during the period examined.

Methodology

Our research examines the impact of the EU's GDPR announcement on April 27, 2016, on the stock performance of American technology companies. To enhance comparability, we divided the firms into two groups: the treatment group includes companies with more than 25% of their revenue from the EU. In contrast, the control group comprises similar-sized firms with less than 25% EU revenue. This segmentation isolates the effects of GDPR based on exposure to EU regulations. By analyzing periods before and after GDPR's announcement, we attempt to link observed effects to the regulatory adoption.

Given the nature of our research question and the panel data, the most appropriate methodological framework is a Difference-in-Differences (DiD) integrated with a two-way fixed effects model Donald & Lang (2007). This approach enables us to control for unobserved, time-invariant differences across firms and time-specific shocks, ensuring our results robustly measure the GDPR's impact. We have employed the following model for our analysis:

$$RET_{it} = \beta 0 + \beta 1 * PostGDPR_t + \beta 2 * EuropePresence_i + \beta 3 * (PostGDPR_t * EuropePresence_i) + \lambda_i + \gamma_t + \varepsilon_{it}$$

Where:

RET_{it} = the daily stock return of firm i at time t, this variable is extracted from the CRSP, and it accounts for cash adjustments, (e.g. dividends paid). Furthermore, it accounts for price adjustments such as stock splits or other corporate actions. This measure is widely used to assess daily stock performance. To ensure clarity, we provide full calculation details of the variable:

Calculation:

For a given day t:

$p(t)$ = Closing price (or bid/ask average) of the stock at time t

$p(t?)$ = Closing price (or bid/ask average) at the last available time before t, which may be up to 10 trading days earlier if no valid prices exist in the interim

$d(t)$ = Cash adjustment (e.g. dividends paid)

$f(t)$ = Price adjustment factor (e.g. splits or other corporate actions)

The daily period return $r(t)$ is computed as:

$r(t) = ([p(t)f(t) + d(t)] \,/\, p(t?)) - 1$ (Appendix A provides further explanation by CRSP)

$PostGDPR_t$ = A dummy variable equal to 1 for April 27, 2016 (GDPR adoption) and all periods after, and 0 otherwise

$EuropePresence_i$ = A dummy variable equal to 1 if firm *i* has a significant presence in Europe (more than 25% of their revenue from the European Union), 0 otherwise

$PostGDPR_t \times EuropePresence_i$ = The interaction term capturing the DiD effect, representing the difference in returns between Treatment and Control groups before and after GDPR.

λ_i = Firm-specific fixed effects (entity effects) to control for time-invariant characteristics of firms

γ_t = Time-specific fixed effects to control for time shocks (e.g. macroeconomic trends).

ε_{it} = The error term capturing unobserved factors affecting returns

An important issue to address before the analysis is multicollinearity, a common challenge when working with panel data models that include two-way fixed effects (TWFE). Multicollinearity arises due to the inclusion of firm fixed effects λ_i and time fixed effects γ_t, which absorb the variation in the individual independent variables $PostGDPR_t$ and $EuropePresence_i$. Specifically, this issue stems from the TWFE framework, where these fixed effects control for all time-invariant firm characteristics and time-specific shocks, respectively.

Entity fixed effects λ_i capture firm-specific characteristics that do not change over time, such as a company's size, intrinsic risk profile, or long-term strategic advantages. For instance, Apple may consistently outperform peers due to its strong brand image and dominant market share. Additionally, structural differences exist between companies providing software solutions versus hardware production—both of which are categorized under the 737 SIC code. By introducing entity fixed effects λ_i, these inherent differences are controlled for in the model, ensuring they do not confound the analysis.

In our case, the variable $EuropePresence_i$ is a firm-specific characteristic that does not vary over time. It indicates whether a firm derived more than 25% of its revenue from Europe in fiscal year 2015. Since this variable is constant within each entity, it is perfectly collinear with the entity fixed effects λ_i and is fully absorbed. Time-fixed effects γ_t, on the other hand, account for shocks or trends that impact all firms at a given point in time. Examples include macroeconomic events like recessions, interest rate changes, or global disruptions such as pandemics. By incorporating time-fixed effects γ_t, our model ensures that these time-specific shocks do not bias the analysis. In our case, the variable $PostGDPR_t$ is a time-specific indicator that varies only across time, marking whether a given observation falls before or after the GDPR announcement on April 27, 2016. As this variable is constant across all entities for a given time period, it is perfectly collinear with the time-fixed effects γ_t and it is fully absorbed.

Unlike STATA, which automatically flags and drops fully absorbed variables, Python requires explicit handling of absorption issues. In our analysis, this was addressed by excluding $EuropePresence_i$ and $PostGDPR_t$ from the model, as they are fully absorbed by the fixed effects. To ensure that this absorption was correctly implemented, we performed diagnostic checks by calculating the residuals of $PostGDPR_t$ after accounting for time-fixed effects and $EuropePresence_i$ after accounting for entity-fixed effects. The near-zero residual variances confirmed the theoretical expectations of absorption. These steps are documented and visually illustrated in Figures 1 and 2 of Appendix B.

For this reason, in the empirical results section, we focus on the interaction term and its coefficient:

$$\beta 3 * (PostGDPR_t * EuropePresence_i)$$

which captures the effect of the GDPR announcement on the returns of firms with significant European presence, controlling for time-invariant firm characteristics and time-specific shocks.

Empirical Results

In this section, the empirical findings concerning the project will be presented. Firstly, we present the result concerning the statistical output of the TWFE DiD model. Secondly, we justify the choice of our model with a visual parallel trends check. Thirdly, we explore a randomized Monte Carlo treatment reassignment with 1,000 iterations.

	Dependent variable: Daily stock returns (**RET**)		
Independent Variable	Estimate	Standard error	P-value
Interaction	0.0004	0.0007	0.5622
No.of observations	22,712		
Entities	68		
Time Periods	334		
Poolability p-value	0.0000		
R^2(overall)	0.0004		

Note. The model includes entity-level and time-level fixed effects.

Table 3: TWFE (Two-Way Fixed Effects) DiD Model Results

The results from the Two-Way Fixed Effects (TWFE) Difference-in-Differences (DiD) model are summarized in Table 3, where the dependent variable is the daily stock returns (RET). The model illustrates the interaction between the GDPR adoption and firms with significant European presence and the effect this interaction has on the daily stock returns. Again, including entity and time-fixed effects allows the model to control for unobserved, time-invariant firm characteristics and time-specific shocks. Appendix B provides the full results of the TWFE DiD analysis.

The coefficient for the interaction term is estimated at 0.0004, with a standard error of 0.0007. The coefficient is positive but low in magnitude. Due to the p-value of 0.5622, the effect is not statistically significant at the conventional α - significance level of 5%. The results suggest that the GDPR adoption did not have a significant effect on stock returns. Therefore, we cannot reject the null hypothesis.

The R^2 value is 0.0004, this indicates that the explanatory power of the model is limited and that only a small portion of the variance of the dependent variable is explained by the independent variable. It is important to note that a low R^2 is not a problem in our model since our primary goal is to isolate and estimate the causal effect. Furthermore, this is expected because we use daily stock returns which are high-frequency financial data denoted by high volatility.

On the other hand, the poolability p-value is 0.0000 which makes it significant at the conventional statistical significance levels (α) - 1%. This result imposes the adequateness of the TWFE statistical framework for our analysis. Precisely, it confirms that accounting for both firm-level fixed effects and time-level fixed effects is essential for delivering robust statistical analysis. Ignoring these fixed effects could result in biased estimates and a lack of credibility concerning the results. Another important notion is that when conducting our statistical analysis in Python, we used clustered standard errors which ensure a robust method of estimating the variability of regression coefficients. In this case, errors were clustered at the entity (firm) level due to the assumption that returns from the same firm are likely to be correlated. By doing so, we account for within-firm correlation, ensuring more robust standard errors and preventing overly optimistic conclusions about the significance of coefficients. Additionally, we also clustered standard errors at the time level to account for potential correlations in returns across firms within the same time period, such as macroeconomic shocks or market-wide trends Petersen (2008).

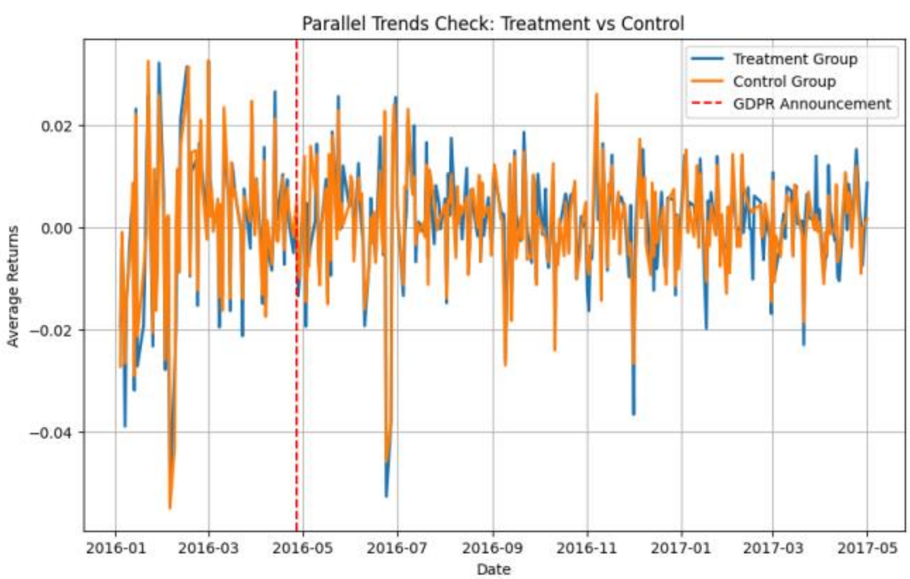

Figure 1: Parallel Trends Check

To justify the choice of our model for the statistical analysis, we conducted a parallel trend check by visually inspecting the average stock returns of our treatment and control group before the GDPR adoption. Figure 1 depicts the average daily stock returns for our treatment and control group over time. The red dashed line signifies the GDPR adoption date (April 27, 2016). Visually, the assumption of parallel trends shall be satisfied since the chart lines move very similarly before the 27th of April 2016.

Monte Carlo

We conducted a Monte Carlo simulation to validate further the observed treatment effect obtained from our Two-Way Fixed Effects (TWFE) DiD model. This approach allows us to assess whether the observed effect of the interaction term is statistically distinguishable from random noise. The idea is to compare the observed effect against a distribution of effects generated under a scenario of random treatment assignment. The treatment group was re-assigned randomly among the firms in the sample while maintaining the same proportion of treated firms as in the original data sample. To be precise, 35 firms in the treatment group and 33 in the control group. Hereby, the structure of the dataset is preserved but the relationship between the outcome and the treatment becomes entirely random. Next, we re-estimate the TWFE DiD model, and subsequently the coefficient of the randomized effect is stored. The number of iterations is 1,000. Afterward, we obtained a distribution of randomized effects under the null hypothesis and the treatment effect is due to randomness. The observed treatment from the original model was compared to this distribution.

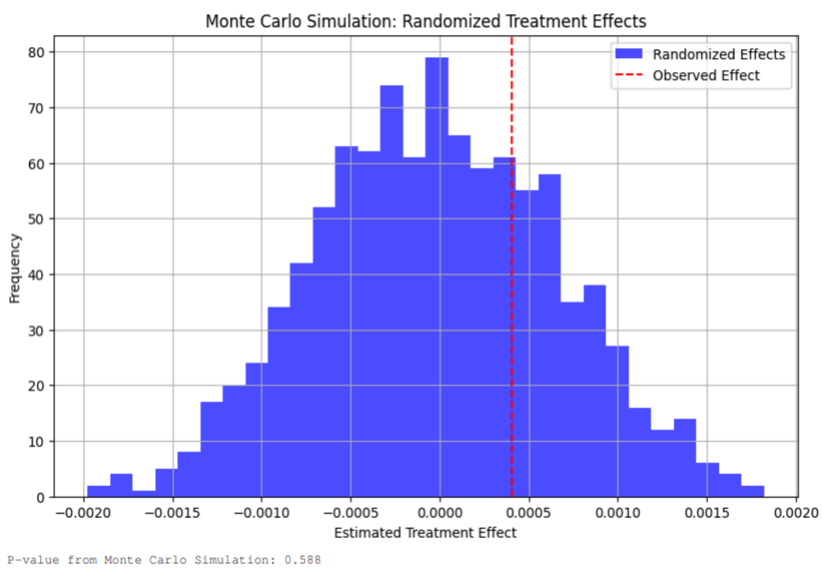

Figure 2: Monte Carlo Simulation - Distribution of Randomized Treatment Effect

Figure 2 presents a histogram illustrating the Monte Carlo simulation results. The observed treatment effect is marked by the red dashed line, while the blue bars represent the frequency of the randomized treatment effects across the 1,000 iterations. The distribution is centered around zero, as expected under the null hypothesis. The error term has an important role in the TWFE model and the Monte Carlo simulation, it serves as a measure of unexplained variability after accounting for fixed effects. In the TWFE framework, the error term is decomposed into three components: entity-specific effects, time-specific effects and an idiosyncratic residual. The inclusion of entity and time-fixed effects accounts for the unobserved systematic variability concerning firm-specific traits and the macroeconomic shocks. Consequently, only random noise is left in the residual. This idiosyncratic error term is preserved in the Monte Carlo simulation which tests the robustness of the observed treatment effect by generating a distribution of randomized effects. By maintaining the integrity of the error term, the Monte Carlo simulation allows for a realistic evaluation of whether the observed interaction term is distinguishable from random variation. This simulation further supports the credibility of our initial estimation, confirming that the coefficient of the interaction term is statistically insignificant. Additionally, it provides a distribution of values that would be expected under random treatment assignment. Importantly, this reinforces confidence in our model, showing that it neither overstates the treatment effect nor misrepresents its statistical significance.

Discussion

In this section, we aim to provide insight concerning the shortcomings of our research and recommendations for future research.

Firstly, our choice of the GDPR announcement date assumes that financial markets are efficient and would likely price in the regulatory risks at the time of the announcement. This approach aligns with prior research in market reactions to policy announcements (Fama, 1970). However, other studies, such as (Arcuri, 2020), focus on the implementation date, arguing that tangible effects materialize as compliance costs and operational changes take effect. While our study provides valuable insights into the announcement's market impact, analyzing the implementation date in future work could offer a more comprehensive understanding. Comparing the announcement and implementation effects may reveal whether markets responded differently to the anticipation versus the realization of GDPR compliance.

Secondly, our methodology utilizes the TWFE DiD framework, which controls for time-invariant firm-specific characteristics and time-specific shocks. While robust, this model has limitations. For instance, our focus on large public companies ensures data reliability but excludes small firms that may have experienced greater compliance burdens relative to their size. Future research could explore the role of the firm size concerning the GDPR's impact on financial performance, providing insights into whether smaller firms faced disproportionate challenges compared to their larger counterparts. Furthemore, the slight difference in the number of firms between the treatment and control groups reflects the natural distribution of U.S. technology firms based on their European market exposure. While the treatment group is slightly larger, this does not compromise the validity of our results, as the TWFE framework compares changes within each group over time. The small imbalance highlights real-world market conditions and ensures external validity, though future research could explore balanced sampling or weighting techniques to test the robustness of these findings.

Lastly, the dynamic nature of financial data demands further sophistication concerning statistical modeling. For example, incorporating dynamic DiD models could capture evolving market reactions. Analyzing cumulative abnormal returns (CARs) across multiple events or assessing long-term impacts beyond the announcement or implementation dates could enrich the findings.

In summary, while this study provides insight regarding the GDPR announcement's impact on stock returns, further research could expand on our findings by exploring alternative timeframes, firm characteristics, and methodological refinements. This would enhance the understanding of regulatory impacts and offer valuable insights for policymakers and investors navigating similar events.

Conclusion

This study examined the impact of the GDPR announcement on the stock returns of American technology companies using a Difference-in-Differences framework with Two-Way Fixed Effects. By dividing firms into treatment and control groups based on their European revenue exposure, we aimed to isolate the effect of GDPR-related regulatory changes. Our findings indicate that the GDPR's announcement did not have a statistically significant impact on the returns of firms in the treatment group compared to the control group.

The robustness of our analysis was supported by a Monte Carlo simulation, which demonstrated that the observed interaction term's effect was consistent with randomized treatment assignments. This reinforces the credibility of our results and the reliability of the model. However, the study has limitations, especially the exclusive focus on large public firms.

Overall, this research contributes to the understanding of how regulatory announcements influence financial markets. It emphasizes the importance of sophisticated econometric methods in disentangling the effects of large-scale policy shifts and provides a foundation for further exploration into the economic implications of data protection regulations.

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Appendix A

Holding Period Return
Variable Name = RET

A return is the change in the total value of an investment in a common stock over some period of time per dollar of initial investment. RET(I) is the return for a sale on day I. It is based on a purchase on the most recent time previous to I when the se curity had a valid price. Usually, this time is I - 1. Returns are calculated as follows:

For time t (a holding period), let:

t? = time of last available price < t

r(t) = return on purchase at t?, sale at t

p(t) = last sale price or closing bid/ask average at time t

d(t) = cash adjustment for t

f(t) = price adjustment factor for t

p(t?) = last sale price or closing bid/ask average at time of last available price < t.

then r(t) = [(p(t)f(t)+d(t))/p(t')]-1

t? is usually one period before t, but t? can be up to ten periods before t if there are no valid prices2 in the interval. A series of special return codes specify the reason a return is missing.

Missing Return Codes

RET(t)	Reason For Missing Return
-66.0	more than 10 periods between time t and the time of the preceding price t?
-77.0	not trading on the current exchange at time t
-88.0	no return, array index t not within range of BEGRET and ENDRET
-99.0	missing return due to missing price at time t

Retrieved from CRSP

Appendix B

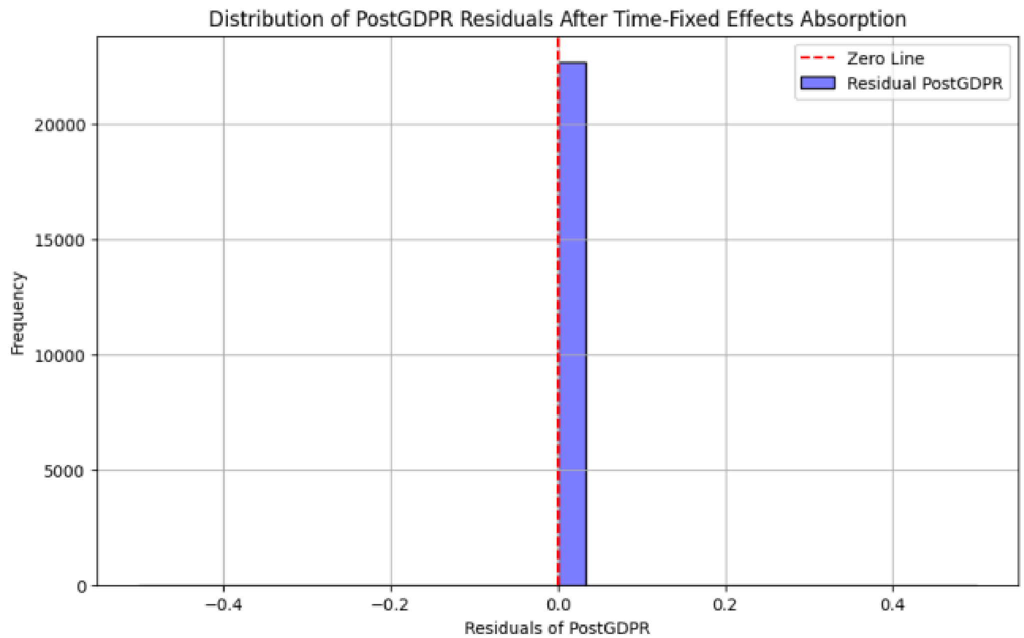

Figure 1: PostGDPR Residuals after Time-Fixed Effects Absorption

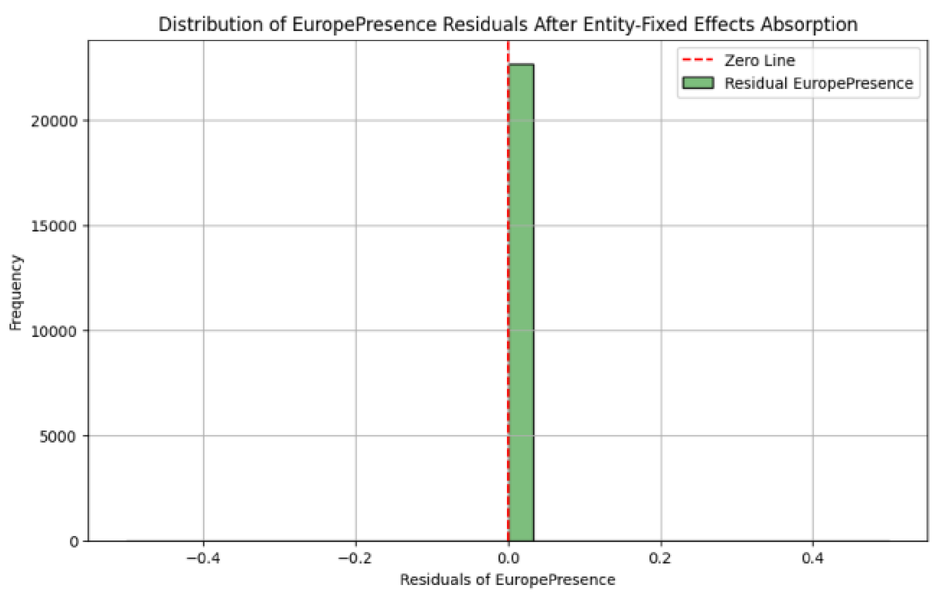

Figure 2: EuropePresence Residuals After Entity-Fixed Effects Absorption

Appendix C

```
Step 3: Two-Way Fixed Effects (TWFE) Analysis

TWFE Model Results:
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:                    RET   R-squared:                     1.903e-05
Estimator:                   PanelOLS   R-squared (Between):              0.1208
No. Observations:               22712   R-squared (Within):               0.0001
Date:                Fri, Nov 29 2024   R-squared (Overall):              0.0004
Time:                        17:11:30   Log-likelihood                 5.708e+04
Cov. Estimator:             Clustered
                                        F-statistic:                      0.4246
Entities:                          68   P-value                           0.5147
Avg Obs:                       334.00   Distribution:                F(1,22310)
Min Obs:                       334.00
Max Obs:                       334.00   F-statistic (robust):             0.3360
                                        P-value                           0.5622
Time periods:                     334   Distribution:                F(1,22310)
Avg Obs:                       68.000
Min Obs:                       68.000
Max Obs:                       68.000

                              Parameter Estimates
===============================================================================
             Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
-------------------------------------------------------------------------------
Interaction     0.0004     0.0007     0.5796     0.5622     -0.0010      0.0018
===============================================================================

F-test for Poolability: 18.664
P-value: 0.0000
Distribution: F(400,22310)

Included effects: Entity, Time
```

Figure 1: Full TWFE DiD results