The Short-Run Effects of GDPR on Technology Venture Investment

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Abstract

The General Data Protection Regulation (GDPR) was enacted in the European Union in April 2016 and went into effect in May 2018. We study its impact on investment in new and emerging technology firms. Our findings indicate negative post-GDPR effects after its 2018 rollout on European ventures, relative to their counterparts in the US and the rest of the world, and considerably lesser effects after its 2016 enactment and before implementation. The negative effects manifest in the number of and amounts raised in financing deals, and are particularly pronounced for newer, data-related, and business-to-consumer ventures.

Keywords: Data, regulation, GDPR, investment, venture financing

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1 Introduction

The rise of big data in the global economy has transformed marketplaces, altering the ways in which firms and consumers interact. Individuals are no longer mere consumers of goods, information and services, but public producers of often valuable data. These data have become key inputs in technology-driven innovation, spanning industry sectors from health, advertising, and security, to e-commerce, transportation, and banking. These data are also key inputs in the matching processes among consumers and firms, as well as between firms and other firms. For individual firms, data is a valuable asset to monetize, especially if the data is personally-identifiable, real-time and of high-frequency. Individuals' traits and attributes, their behaviors and online footprints, their comments and photos, their work and leisure habits, and more, are increasingly regarded as business assets that can be used to target services or offers, to provide relevant advertising, financial offerings, and healthcare, or to trade with other parties.

In an effort to leverage the value inherent in the data created by individuals, new services, companies, and markets are emerging. The services, tools, and products being made possible by the increased availability of data are bearing benefits for data subjects and data holders alike. These benefits include tailor-made recommendations, digital personal assistants, new products and offerings, and easy access to previously thin or unavailable markets. The Federal Trade Commission's 2016 report on big data (FTC, 2016) highlights a number of benefits to underserved populations, including increased educational attainment, access to credit through non-traditional methods, specialized health care for underserved communities, and better access to employment.

Despite those benefits, public concerns over the use of personal data have increased. Recent Pew surveys find that 91% of respondents believe they have lost control over how personal information is collected and used, 61% would like to do more to protect their privacy, and 66% said current laws are insufficient for protecting their privacy and would support more regulation.[1] These concerns are amplified by recent incidences of data breaches and data misuses, and a lack of regulatory actions after these scandals.

Those concerns are not without merit. The Commission's earlier report (FTC, 2014) indicates that data brokers collect and store billions of data elements covering nearly every US consumer, with one data broker holding information on more than 1.4 billion consumer transactions and 700 billion data elements, while another broker added more than 3 billion new data points to its database each month. Another report found that 95% of the top 200 free iOS and Android apps exhibit at least one risky behavior including location tracking, access to social networks, and disclosing the user's personally identifiable information.[2] The FTC's 2016 report also highlights possible risks that could result from biases or inaccuracies about certain groups, including more individuals mistakenly denied opportunities based on the actions of others, sensitive information being exposed, existing disparities being reinforced, increased targeting of vulnerable consumers for reasons such as fraud, an increase in prices for goods and services in lower-income communities, and the weakening of consumer choice.

Against this backdrop, the General Data Protection Regulation was adopted in the European Union on April 14, 2016, becoming enforceable two years later on May 25, 2018. The regulation aims to protect data by 'design and default,' wherein firms are obligated to handle data according to a set of principles and safeguards. GDPR mandates a higher degree of privacy, data management, and control, requires legitimate interest or informed opt-in consent for data collection, and assigns substantial liability risks and penalties for data flow and data processing violations. Under the regulation, firms that process personal information must develop protocols to respond to individual data requests within a month, appoint a data protection officer to oversee compliance activities, audit internal data processes, and take proactive steps to anonymize and secure personal data and minimize its collection. In

[1] http://www.pewresearch.org/fact-tank/2018/03/27/americans-complicated-feelings-about-social-media-in-an-era-of-privacy-concerns/

[2] https://www.appthority.com/company/press/press-releases/appthority-exposes-security-and-privacy-risks-behind-top-400-mobile-apps/

the event of a data breach, organizations must promptly notify the regulator and affected individuals. The regulation requires that users have the rights to access, correct, and erase their personal data, and imposes fines up to 4% of global revenue for any violation.[3]

The regulation may affect ventures in multiple ways. First, ventures may encounter challenges in dealing with procedural issues in the implementation of compliance. Second, to the extent ventures can comply with GDPR, one possible channel could be that greater data costs, in terms of access, collection, liability, and commercialization directly affect business models and indirectly increase customer acquisition costs.[4] Ventures may also rely on the compliance strategies of larger platforms to guide their data-related liabilities, and the compliance costs of doing business may increase. Moreover, due to lack of clarity about acceptable forms of compliance and the associated risks of enforcement, the extent of the increase in compliance costs may be ex-ante uncertain. For instance, the regulation creates uncertainty with respect to which data-driven products are compliant, and whether products or processes need to be changed, since compliance itself is a function of heuristics that have yet to be fully tested in courts (e.g., ventures and investors may be unclear about whether legitimate interest versus informed consent is an adequate path to compliance).

GDPR is particularly likely to influence technology firms, given an ever increasing need for the use of data as a core product input. There appear to be at least two broad categories

[3]On June 28, 2018, California adopted a data regulation law (the California Consumer Privacy Act of 2018, A.B. 375) that is set to take effect on January 1 2020. The law, as currently written, would require that firms provide consumers with the ability to port their profiles to other providers, be informed about what personal data are stored about them, why they are collected, request their deletion, and opt out of their sale. The legislation is still subject to amendments, and it is widely understood that the version that was passed is highly likely to change based on input from stakeholders before its implementation in 2020. On November 1, 2018, Senator Ron Wyden's office began circulating a discussion draft of a bill tentatively-named the "Consumer Data Protection Act," which aims to introduce similar and other protections at the federal level. Another draft bill began circulating on December 12, 2018, proposed by a group of 15 Democratic senators.

[4]In the Ernst & Young 2018 Annual Privacy Governance Report (`https://go.ey.com/3cwtoYu`), the average respondent indicated it would spend a total of $3MM in 2018 as a result of GDPR, with financial and technology firms being the biggest spenders. A survey by Netsparker (`https://bit.ly/2XOMKDS`) indicates the the majority of US businesses surveyed would spend $50k–$1MM to comply with the regulation, suggesting a potentially costly sum in relative terms for smaller ventures—as well as for EU firms that, in comparison to their US counterparts, would find it more challenging to reduce or deprecate their EU consumer footprint. A 2019 survey by GDPR.EU (`https://gdpr.eu/2019-small-business-survey/`) further indicates that compliance investments are non-negligible for smaller businesses.

for how GDPR can affect business. The first includes costs related to adjusting a firm's business model such that it meets regulatory requirements. The second includes potential reductions in longer-term profitability due to costs related to maintaining different systems, higher fines, or the inability to extract the same amount of value as in the pre-GDPR regime.[5]

This study presents an analysis of the impact of GDPR on new technology venture investment in the EU. Our analysis suggests that, for some ventures, GDPR compliance may entail costs that are responsive to both of the aforementioned categories at the outset. For other ventures, costs seem to be realized primarily after GDPR's rollout. Specifically, our findings indicate negative differential effects on EU ventures after the rollout of GDPR (i.e., after the start of its enforcement on May 25 2018) relative to their counterparts in the US and the rest of the world (primarily comprising venture deals in Australia, Canada, China, Israel, India, Japan, Russia, and South Korea), but considerably lesser effects after GDPR's enactment (i.e., after its adoption on April 14, 2016). The negative effects manifest in the number of financing rounds, which, after GDPR's rollout, exhibit a 26.1% reduction in the number of monthly venture deals by EU ventures compared to their US counterparts. A comparison between EU ventures and their counterparts in the rest of the world not including the US also points to a similar large negative effect. The negative effects are larger in the 6 months period immediately after GDPR's rollout in 2018, but some of them are sustained in the proceeding 6 months. Furthermore, our analysis suggests that consumer-facing ventures also incur significant deal reductions after GDPR's enactment—for the subset of consumer-facing ventures that tend to handle data, those reductions are as high as 15.8%.

We proceed to break down these effects in multiple ways. First, by sorting financing deals into two groups, those made for more data-related and less data-related ventures. Second, by sorting deals into those made for business-to-consumer (B2C) ventures and those made for business-to-business (B2B) ventures. Third, by sorting deals into three (early, main,

[5]We note that if a major platform on which ventures tend to rely releases substantively new policies for the purpose of GDPR compliance, and those policies impact the business models of ventures as well as their longer-term profitability, then both categories may be responsive to the platform's GDPR-related policy changes.

late) funding stages. Fourth, by sorting deals based on several firm age groups (0-3, 3-6, 6-9, and 9+ year old). And fifth, by sorting firms into four industry categories (health, finance, information technology, and other).

We find that ventures whose products tend to be more reliant on data exhibit somewhat larger negative effects, with reductions of about 31% in the monthly number of EU venture deals relative to both their US counterparts and counterparts in the rest of the world. We also find that consumer-facing ventures incur larger declines than business-facing ventures. For instance, relative to their US counterparts, the monthly number of EU B2C deals decreases by 4.2% after the 2016 enactment of GDPR and by 17.6% after its 2018 rollout (and, as previously mentioned, more so when focusing on B2C deals by more data-related ventures); B2B deals, in comparison, did not significantly change after GDPR's enactment but decreased by 10.8% following its rollout. The difference between B2C and B2B ventures is potentially because consumer-facing products have more exposure to the regulation, particularly to its requirements concerning individual users (e.g., opt in or legitimate interest, data management, control, and processing violations, with potential fines per violation). We further find that the negative effects of GDPR's rollout on technology investment appear particularly pervasive in earlier-stage deals (exhibiting a 34% reduction relative to US ventures) and for newer, 0-3 year old ventures (a 30.3% reduction relative to the US). We also identify negative effects for ventures that fall under the healthcare and finance categories, with 26.1% and 21.3% reductions, respectively, in the monthly number of EU deals in those categories in comparison to US ventures. We demonstrate that the results are robust to a number of specifications, different control groups, and to other potential explanations, including the Cambridge Analytica scandal.

1.1 Literature Review

The literature that examines the implications of data policies and data regulation is growing (Acquisti et al., 2016, offer a recent survey). Our work is closely related to Goldfarb and

Tucker (2011) and Lambrecht (2017). These papers study the effects of earlier EU privacy policies associated with the EU's Privacy Directive. Goldfarb and Tucker examine the effects of the 2003 and 2004 implementations of the Privacy Directive across EU member countries, which limited the ability of advertising networks to collect user data in order to target ads, and demonstrate that, after they took effect, advertising effectiveness in the EU decreased significantly. Their study uses the responses of 3.3 million survey-takers who had been randomly exposed to 9,596 online banner ad campaigns. For each of the 9,596 campaigns, their dataset contains a treatment group exposed to the ads and a control group exposed to a public service ad. To measure ad effectiveness, they use a short survey conducted with both groups of users about their purchase intent towards an advertised product. They find that, following the ePrivacy Directive, banner ads experienced a reduction in effectiveness of over 65%, with no similar changes in non-European countries during a similar timeframe. It is thus possible that data rights, such as the ones put forward by GDPR, can have detrimental effects on revenues from online advertising. Goldfarb and Tucker draw the implication that digitization may mean that privacy policy could now be a part of innovation policy, an assertion to which our analysis lends further credence.

Lambrecht (2017) studies a setting that is similar to ours but in the context of the earlier EU's 2002 Privacy Directive and using a smaller dataset. Her study assesses the impact of the Directive on venture capital investments and derives results that are in line with our study. Lambrecht argues that innovation in online advertising has increasingly benefited from the ability to predict consumer preferences using data, and finds that the 2002 Privacy Directive was associated with significant negative effects on the financing of predominately smaller EU ventures in the categories of online advertising, online news, and cloud computing. Lambrecht asserts that the Directive may have led firms to invest disproportionately in complying with its guidelines, or decide not to serve potential customer segments, consequently depressing their revenue and growth prospects, in turn diminishing investments in those venture categories.

This paper is also related to a recent line of work that examines other GDPR effects. Among those, Goldberg et al. (2019) and Johnson and Shriver (2019) examine the impact of GDPR on online web traffic, sales, and third-party tracking. Using proprietary datasets, they show that for EU firms, recorded pageviews fall by 7.5%, recorded conversions fall 12.5%, third-party tracking falls 6.2%, and the use of tracking vendors concentrates on fewer vendors after the rollout of GDPR.[6] They demonstrate that beliefs about local regulatory strictness play a factor in firms' reactions, with results that are complementary to our findings. Specifically, while their focus is on the health and regulatory compliance of both online publishers and e-commerce sites, our focus is on the broader tradeoff between innovation and data regulation, for which specific considerations such as ad tracking are one of many data monetization components. Moreover, rather than focus on existing firms, our study focuses on emerging ventures that are typically smaller.

In this regard, our analysis tests predictions from the theoretical works of Krasteva et al. (2015) and Campbell et al. (2015), who show that compliance costs and data regulation, respectively, can create barriers to entry and may thus hurt innovation. In particular, Campbell et al. (2015) show that though privacy regulation imposes costs on all firms, it is small firms and new firms that are most adversely affected, particularly for goods where the price mechanism does not mediate the effect, such as the advertising-supported internet. Krasteva et al. (2015) show that as the costs of compliance by small firms increase, more innovations will be developed within established firms.[7]

Several other papers have studied the impact of GDPR in other domains. Batikas et al. (2020) demonstrate that websites reduced their connections, particularly regarding re-

[6] In a related paper, Tucker (2014) uses a randomized field experiment to show that users are more likely to click on personalized ads once they are given more control over their personally identifiable information, a change that was only driven by the change of user perception of privacy control, as the website did not change how advertisers used data to target and personalize ads.

[7] While one may argue that higher compliance costs may have a positive effect on innovation (e.g., Porter, 1991), Jaffe and Palmer (1997) find little evidence that industries' inventive output (as measured by patent applications) is related to compliance costs. At the same time, Adjerid and de Matos (2019) find that opt-in consent provision by consumers for data collection increased for a large (incumbent) telecommunication provider after GDPR took effect.

quests involving personal data, to web technology providers after GDPR's rollout, potentially leading to an increase in market concentration in web technology services. Aridor et al. (2020) estimate an approximately 12.5% reduction in the number of persistent trackers available to a major ad network in the EU travel industry after the rollout of GDPR. Their findings suggest that consumers are making use of the increased opt-in capabilities mandated by GDPR and that an established major firm may be able to sustain these losses through improved analytics and better tracking of users who do opt in. Their findings lend support to the argument that consent denial diminishes firms' capability to track consumers across websites, hampering their ability to target ads and offers, potentially leading to revenue losses among firms that rely on consumer data. In combination with theirs, our findings suggest that nascent ventures may be less able to sustain such revenue losses, as indicated from investors reducing their investments in new EU ventures.

The prior empirical literature that studies the impact of privacy regulation is relatively small. In healthcare markets, using variations in state laws, Miller and Tucker (2009, 2011) show that certain state privacy regulations (adopted above minimum federal requirements) that restrict a hospital's release of patient information diminished the adoption of electronic medical records, due to reduced network effects from adoption, in turn reducing market efficiency. [8] In financial markets, Kim and Wagman (2015) theoretically show that an opt-in approach for information trade in financial markets can lead to higher prices, and empirically demonstrate their results in the market for mortgages, with indications of higher mortgage rates, lower mortgage underwriting standards, and potential downstream foreclosures.[9]

[8] A related issue is an insurer's access to information about a person's genetic test results and subsequent price discrimination. In the US, most states have banned the use of genetic information by health insurers; however, some theoretical results show that inefficiencies may arise when test information is private relative to when it is public (Hoel and Iversen, 2002), and some empirical findings identify relationships among how consumers are informed, the control they have over their private information, and whether consumers elect to partake in genetic testing and share their information with providers (Miller and Tucker, 2017). In the case of health information exchanges, other work highlights that privacy regulation can in fact increase positive economic outcomes, particularly with respect to technology innovation (Adjerid et al., 2016).

[9] Pagano and Jappelli (1993, 2002) relatedly predict that if banks share information about their customers, they would increase lending to safe borrowers, thereby decreasing default rates. Other studies focus on the effects of credit bureaus and creditor rights using data from a cross-section of countries (see, e.g., Djankov et al. 2007; Qian and Strahan 2007). Hertzberg et al. (2011) and Doblas-Madrid and Minetti (2013) analyze

The aforementioned works largely examine a specific aspect or implication of data regulation, such as advertising, pricing, defaults in financial markets, and the impact on medical effectiveness, or even a specific industry or company. Our work is complementary, in that our analysis centers around the effect of data regulation on technology ventures and the nascent firms that data regulation is most likely to affect. Moreover, since technology cuts across sectors, our analysis is in some sense broader, and demonstrates that younger firms are particularly susceptible to the consequences of data regulation.[10]

The remainder of the paper proceeds as follows. Section 2 describes the data and Section 3 presents the overall empirical approach. Section 4 provides results at the aggregate level, and Section 5 gives subsample results broken down by industry category, funding stage, firm age, data proximity, and business type. Section 6 presents several extensions and robustness tests, and Section 7 concludes. Analyses of GDPR effects on the aggregate and deal-level amounts invested are in the appendix.

2 Data

Our primary data sources are the Crunchbase (CB) and VentureXpert (VX) datasets. CB is a platform for tracking information about technology businesses, particularly nascent ventures, and VX is a comprehensive dataset of venture capital investments.[11] We collect data on all technology-venture related activity in the EU, US, and the rest of the world (RoW) from January 2014 to April 2019, including the parameters of venture financing rounds, such as venture information (name, location, operating category, founding date, and financing dates) and funding information (the size of a funding round, the date a round was announced, the

micro data to show that the effect of lenders' information sharing is to reduce incidence of delinquencies and defaults, but lenders may reduce credit in anticipation of other lenders' reaction to negative news.

[10]Our findings are thus in line with Kortum and Lerner (2000) who show that the industrial innovations that venture capitalists help facilitate is a multiple of the ratio of venture capital to R&D expenditures, as well as with Kerr et al. (2014), who suggest that the bundle of inputs that angel investors provide have a large and significant impact on the success and survival of new ventures.

[11]For recent activity in the academic literature that pertains to CB, see Hochberg (2016), Kaplan and Lerner (2017), Lerner et al. (2018), and Chatterji et al. (2018). For recent activity that pertains to VX, see Cumming and Dai (2010), Hochberg et al. (2010), and Nahata et al. (2014).

type of financing such as seed, Series A, Series B, and the number, names, locations, and types of the participating investors).

Each venture in the CB dataset is also tagged with relevant product keywords (e.g., 'software', 'e-commerce', 'finance', etc) that we utilize to form different groupings of venture deals and to adjoin the datasets. The VX dataset groups ventures into three industries (information technology, medical/health care/life science, and non-high tech) and provides a business description for each venture with relevant keywords, in line with the CB keywords.[12] The adjoining of the two datasets is completed in several steps. First by sorting ventures' financing deals into three (early, main, and late) funding stages, a relatively straightforward process since CB and VX each have a more detailed breakdown of funding stages.[13] Second, by matching ventures' keywords in CB to industry keywords in VX to identify each CB venture's corresponding industry. Third, ventures from both datasets with finance-related keywords (e.g., finance, banking, payment, accounting, financial service) are grouped into a fourth 'finance' category.[14] Sensitivity analyses are run for each of these steps.[15]

Our findings hold for the CB and VX datasets separately, but their adjoining is advantageous because the two are complementary. Specifically, CB data has a relatively large number of angel and earlier, seed-stage investments. The VX dataset has a relatively large

[12]We focus on ventures in the funding stages that VX classifies as 'Startup/Seed', 'Early Stage', 'Expansion', or 'Later Stage', which excludes 6,104 deals classified under 'Real Estate' or 'Other' funding stages.

[13]The two datasets categorize funding stages differently. VX has 6 major funding stage groups (startup/seed, early stage, expansion stage, buyout/acquisition, later stage, and other financing stages) whereas CB has more specific stages (e.g., angel, seed, series A, series B, private equity, post IPO, debt financing, etc). Early stage comprises angel, seed, pre-seed, convertible note, and product crowdfunding stages from CB, and startup/seed and early stages from VX. Main stage comprises series A, B, C, bridge series A-B, initial coin offering, and equity crowdfunding from CB, and expansion and acquisition stages from VX. Later stage comprises series D and later, private equity, debt financing, and post IPO activities from CB, and later stage from VX. The precise grouping of funding types does not change the nature of the results.

[14]The matching processes compare venture keywords in CB to identify in which category they show up in the business descriptions of ventures from VX. For instance, if a CB venture's keyword shows up in the description of VX ventures under the healthcare category, the CB venture is categorized under healthcare. In cases where there are multiple matches, we prioritize healthcare, then finance, then information technology, and use a threshold to determine prioritization in the relatively few events of multiple categories, and run sensitivity tests on the choice of the threshold, which point to no effect on the results.

[15]In addition, we assessed whether CB and VX's efforts to complete certain variables have changed conditional on them having the observations. We did so by using a placebo test for deals that are missing (i) dollar amount only, and for deals that are missing (ii) both dollar amount and investor information. We find that whether a variable is missing in our placebo test bears no relationship to GDPR's rollout.

number of venture-capital investments and deals in other funding stages. From January 2014 through April 2019, there are 91,764 CB and 66,673 VX financing deals; of those, 18,432 (approximately 13.17%) overlap.[16] The focus areas of the two datasets are also noticeable in the distribution of the early (comprising 45% CB of deals, 31% of VX), main (33% of CB, 48% of VX), and later (22% of CB, 21% of VX) funding stages.

Given that CB does not provide an industry categorization for ventures, our focus is on the VX-mappable categories of healthcare, finance, information technology, and others. We select these crude categories in part because healthcare and finance tend to be subject to industry-specific regulations,[17] thus comparing them against other technology firms allows us to detect a potentially differential effect of GDPR on healthcare-financial firms. Another reason is that the industry mix of ventures varies greatly across states (US states and EU member states), but every state has at least one deal in each of the four crude categories throughout the sample. Hence, the four-category grouping helps us construct a balanced sample by month, state and category. The results are not sensitive to the precise grouping (an unsupervised clustering approach yielded similar findings). The category distributions in both datasets are quite similar, with 16.85% of deals in healthcare, 10.77% in finance, 61.52% in information technology (IT), and the remaining 10.86% in the 'other' group.

We treat each funding round observed as a 'deal' event, tallying deals per month in each crude industry category and in each US or EU member state.[18] Separately, we group all firms that are tagged with data-related keywords (such as 'data,' 'statistics,' 'location-based services,' 'AI,' 'social media,' and e-commerce) into a 'more-data related' group; all

[16]Some venture names need to be matched between the two datasets due to small differences. For instance, a venture named "ABC" in CB may appear as "ABC Inc." in VX. The matching process is such that the search for matching keywords is automated but any 'approved' match is done manually.

[17]In the US, the Health Insurance Portability and Accountability Act (HIPAA) governs data collection, data use and data security for health care, and the Gramm-Leach-Bliley (GLB) Act governs similar issues for finance.

[18]Despite Brexit, we include Great Britain as part of the treatment group due to its adoption of a GDPR-like regulation in the same time frame as the rest of the EU, and due to the fact that it is still bound by GDPR during our sample. In addition, the few observations we have for Bulgaria, Cyprus, Malta, and Lithuania are removed because some macroeconomic variables were not available for those member states at monthly frequencies.

other ventures are grouped into a 'less-data related' group.[19] We similarly identify 'B2C-focused' and 'B2B-focused' ventures in an analogous way based on relevant keywords (such as 'B2C,' 'consumers,' and 'individuals' for the B2C category; and 'enterprise,' 'business,' and 'Software as a Service' for B2B). We further collect local macroeconomic controls such as unemployment rate, CPI, interest rate, median income, stock index, and GDP per capita for each member state in which a venture is located.

Adopting an approach from Goldberg et al. (2019), we incorporate a measure of regulatory strictness by making use of the European Commission's 2008 survey of 4,835 data controllers:[20] "Data Protection in the European Union: Data Controllers[21] Perceptions." Specifically, we use question Q3B of the survey: "The data protection law in (OUR COUNTRY) is interpreted and applied more rigorously than in other Member States." Respondents either totally agreed, rather agreed, rather disagreed, totally disagreed, or abstained, and the survey results provide the percentage of respondents who selected each answer in each EU member state.[22] The continuous and time-invariant measure on which we focus is the proportion of respondents who either 'agreed' or 'rather agreed' with the survey's statement.

There are 140,005 deal observations in the combined sample of EU and US venture deals without duplicates. Of those, 39,605 CB observations are missing dollar amounts, 3,004 observations in CB and VX are missing a funding stage (a control at the deal level), and 4,465 CB deals are missing both dollar amounts and investor information (e.g., investor name, investor location, investor type). Some VX observations do not have investor names but they do contain all of the other investor fields. Observations with missing dollar amounts (and missing funding stages at the deal level) are omitted from dollar-amount specifications. Number-of-deals specifications only omit the 4,465 observations missing both dollar amounts

[19]While this categorization is rather crude, it captures our intent to roughly categorize firms by how critical data is to their operations. The results are not sensitive to the precise set of keywords we use.

[20]See: `http://ec.europa.eu/commfrontoffice/publicopinion/flash/fl_226_en.pdf`

[21]The data controller is the principal party responsible for collecting consent, managing consent revocation, and enabling right to access. Controllers need to assess any risks to individuals posed by their processing activities. The requirements also identify common factors for controllers when making assessments, such as state-of-the-art technology, cost of implementation, and the nature, scope and purposes of data processing.

[22]Abstention survey responses are omitted from the denominator.

and all investor information. We calculate a venture's time-varying age based on its founding date.[23] We consider four different age categories: new firms (0-3 years old), young firms (3-6 years old), established firms (6-9 years old), and mature firms (9+ years old). Firms may consequently switch between age categories in our sample.

Table 1 reports the summary statistics in the EU and US. Panel A indicates that our sample comprises 24 EU member states and 51 US states with the District of Columbia (henceforth, states). On average, both the monthly dollar amount raised (in millions) and the number of deals per state per category are similar between the EU and US. The average dollar amount raised per deal in our sample in the US (about $22.18 million) doubles that in the EU (about $11.15 million). The distribution is highly skewed in both the EU and US, with the median dollar amount raised per deal ($2.19 million for the US and $0.96 million for the EU) much lower than the average. The average firm age is about 3 years in both the EU and US when excluding more mature (9+ year old) firms.

Panels B, C, D, and E report summary statistics for each of the subgroups we track. Panel C, for instance, reports summary statistics for more-data and less-data related ventures, as well as B2C and B2B ventures. Deal size tends to be smaller for more-data related and B2C compared to less-data related and B2B ventures, respectively. Panel D suggests that most funding deals in our sample take place in either the early stage or the main stage. Panel E provides information about the distribution of firm age in our dataset. While they are similar, the US has a larger proportion of deals in 9+ year old firms. The EU, in contrast, has a larger proportion of deals in the 0-3 and 3-6 age groups—firms that may be particularly susceptible to an increase in the costs of compliance. Of particular interest is the fact that close to 70% of ventures in the EU and US in our sample are relatively young, 0-6 year old ventures. It is also apparent that the older the firm, the higher the average dollar amount raised per deal. Figures 1(a) and 1(b) depict monthly trends for the number of deals and dollar amount raised. There are no noticeable differential trends in the EU and US.

[23] There are some cases where a founding date is unavailable or when a venture's first financing round predates its founding; in those cases, we use the venture's first financing round as its founding date.

For the purpose of an alternate control group, we further collect data on deals from January 2014 through April 2019 from CB and VX for investments in non-EU-non-US ventures in the rest of the world (RoW). In this RoW group, there are 12 countries with more than 1000 deals, 43 countries with 50-1000 deals, and 97 countries with fewer than 50 deals. The latter group is omitted from the sample due to their relatively few observations and our inability to locate their monthly or quarterly macroeconomic variables. The 43 countries with 50-1000 deals are grouped together into an "other country" group, for which macroeconomic variables are computed as the population-weighted average of the respective variables for each country in the group. Table 2 reports RoW summary statistics.[24]

3 Empirical Approach

We aim to study the effects of GDPR on venture financing in the EU. In line with Goldfarb and Tucker (2011, 2012), we do so by contrasting venture activity in the EU with the US before and after both the passage and rollout of GDPR. While GDPR was enacted in April 2016, its enforceability began to take hold in May 2018, with mandatory implementation by EU member states and mandatory compliance by firms. Our hypothesis is that as GDPR's enforceability came into place, entrepreneurs and investors both realized the actual compliance and implementation costs, as well as the ex-post implications of GDPR. This is particularly evident in the days and weeks immediately before GDPR's effective date, as major platforms, including Google, Facebook, Amazon, Apple, and Shopify, on which a vast number of technology ventures rely, began to reveal the ways in which they were tightening their platforms and app stores with new data sharing, data portability, and data liability rules.[25]

[24]Due to a wider variety of countries in the RoW group, in terms of subgroups, our focus is on grouping more-data related and less-data related ventures (rather than categorizing by healthcare, finance, information technology, and other) since this distinction may depend less on industry-country-specific regulations.

[25]Examples include SafeDK in 1/25/18 documenting that more than half of mobile applications are not GDPR ready (https://www.mobilemarketer.com/news/study-55-of-apps-may-not-meet-gdpr-privacy-standards/515546/), and numerous examples from May 2018. Those include Apple reportedly removing apps that share location data (https://www.idownloadblog.com/2018/05/09/apple-removing-apps-location-

We test the effect of GDPR using a difference-in-differences methodology (DID). Our main focus is on the aggregate level, where each observation is defined at the month-state-category level, and the dependent variable is the number of deals reached in a month-state-category. The dependent variable could be zero if no venture in the state had any deal in that month-state-category.[26]

Our treatment group comprises EU ventures and our primary control group comprises US ventures, with RoW ventures as an alternate control group. While the treatment group does have lower levels of venture activity than the US control group, there does not appear to be a differential pre-trend that would violate the common trend assumption in our DID analysis. Figures 1(a) and 1(b) suggest that no apparent divergence took place between the treatment and control groups after the enactment of GDPR, but some sustained divergence took place around the time that GDPR was rolled out. The trends track each other closely otherwise up until May 2018. Our specification is given by:

$$y_{sct} = \alpha_s + \alpha_c + \alpha_t + \delta X_{st} + \beta_1 EU_s \times GDPR\_Enact_t + \beta_2 EU_s \times GDPR\_Rollout_t + \varepsilon_{sct}, \quad (1)$$

where s denotes state, c denotes industry category, t indexes month, EU_s is a dummy that equals 1 for EU states and 0 otherwise, $GDPR\_Enact_{ct}$ is a dummy variable that equals 1 if the time t is on or after April 2016 but before May 2018 and 0 otherwise, and $GDPR\_Rollout_{ct}$ is a dummy variable that equals 1 if the time t is after May 2018 and 0 otherwise. The dependent variable of interest is Y_{sct}, which is the number of financing deals in each month-state-category. Year-month, state and category fixed effects are denoted by

data/) and updating its privacy terms (https://techcrunch.com/2018/05/23/apple-introduces-new-privacy-portal-to-comply-with-gdpr/), Facebook announcing that "Businesses may want to implement code that creates a banner and requires affirmative consent? Each company is responsible for ensuring their own compliance" (https://developers.facebook.com/ads/blog/post/2018/05/10/compliance-protections-gdpr/), Shopify updating its app permissions for merchants and developers (https://www.shopify.com/partners/blog/gdpr-compliance), Google releasing new consent requirements to developers (https://bit.ly/2ziUgJA), all shortly before GDPR took effect on May 25, 2018.

[26] We separate deals at the state level since: i) The implementation of GDPR, while aiming for a uniform law, is local (i.e., country-level enforcement in EU). ii) There is no US federal privacy legislation except for select age groups or sectors such as healthcare and finance. iii) Each EU member state is not comparable with the US at the macro level, and some macro variables such as unemployment are local.

α_t, α_s and α_c, respectively, whereas X_{st} are state-specific macroeconomic control variables (monthly unemployment rate, CPI, interest rate, stock index, and quarterly GDP per capita and median income[27]), and ε_{sct} is an error term. The coefficients β_1 and β_2 capture the effects of GDPR's enactment and rollout across all categories, respectively. Standard errors are clustered at the state level, because GDPR mandates state-specific enforcement and the heterogeneity is confirmed in market perception.[28] We use a Poisson specification for the number of deals regressions due to a relatively large number of zeroes at the month-category-state observation level. In all cases, we obtain similar results with OLS and linear median regressions.

In line with Autor (2003), we run a lead/lag treatment effect analysis for the EU sample on a quarterly basis. Figure 2 depicts coefficient plots of the quarterly pre-treatment tests for the number of deals using Poisson specifications. To perform the pre-treatment tests, we run the same specifications for the pre-GDPR enactment data, including a full set of interactions between the EU dummy and each quarter dummy. The coefficients of these interactions are depicted in the figure, along with their confidence intervals. Figure 2 indicates that there is no pre-existing differential trend between the EU and US in the number of deals per month prior to April 2016, confirming the trends observed in Figure 1.[29] Figure 2 also suggests that there is no significant impact from the enactment of GDPR but a significant and larger negative effect on the number of venture financing deals after the rollout of GDPR.

We further test the effects of GDPR for different subgroups of ventures, separately ap-

[27]The results continue to hold when not controlling for these macroeconomics variables.

[28]Despite GDPR applying to all EU countries, the policy change is at the state level. This follows from the definition of the 'lead supervisory authority,' which has the "primary responsibility for dealing with a cross-border data processing activity, for example when a data subject makes a complaint about the processing of his or her personal data." The location of the lead supervisory authority is based on a firm's main establishment location. Recital 127 further states that: "Each supervisory authority not acting as the lead supervisory authority should be competent to handle local cases where the controller or processor is established in more than one Member State, but the subject matter of the specific processing concerns only processing carried out in a single Member State and involves only data subjects in that single Member State." Goldberg et al. (2019) additionally demonstrate that GDPR suffers from implementation heterogeneity across EU countries, heterogeneity that lines up with traditional member state enforcement behaviors.

[29]We include the months of April 2016 in the post-enactment period and May 2018 in the pre-rollout period. The results are unchanged if we remove these months from the sample.

plying the same specifications to the venture categories of health, finance, information technology, and other; more-data-related and less-data-related firms; B2C and B2B ventures; different funding stages (early, main, late); and different venture age groups (0-3, 3-6, 6-9, 9+ years old). In extensions, we also assess the effects of GDPR on the amounts raised per month and per deal using different dependent variables.

In addition, to take into account the potentially different enforcement protocols, strategies and levels of strictness of supervisory authorities in different EU member states—at the very least as ex-ante perceived by investors—we incorporate an additional measure of regulatory strictness, making use of the European Commission's 2008 survey of 4,835 data controllers. The survey results suggest that a third of respondents believed the data protection laws in their country were applied more rigorously than in other member states, with a quarter saying the opposite. More developed countries such as France, Germany, and the UK tend to be correlated with perceptions of greater regulatory strictness. To decouple the effect of regulatory strictness from GDP per capita, we use the following specification (where GDP refers to GDP per capita):[30]

$$\begin{aligned} y_{sct} = {} & \alpha_s + \alpha_c + \alpha_t + \delta X_{st} + \beta_1 EU_s \times GDPR\_Enact_t + \beta_2 EU_s \times GDPR\_Rollout_t \\ & + \beta_3 RS_s \times GDPR\_Enact_t + \beta_4 RS_s \times GDPR\_Rollout_t \\ & + \beta_5 GDP \times EU_s + \beta_6 GDP \times GDPR\_Enact_t + \beta_7 GDP \times GDPR\_Enact_t \\ & + \beta_8 GDP \times EU_s \times GDPR\_Enact_t + \beta_9 GDP \times EU_s \times GDPR\_Rollout_t + \varepsilon_{sct} \end{aligned} \tag{2}$$

In (2), RS_s gives the proportion of survey respondents in each EU member state who believe their supervisory authority is relatively strict (we set $RS = 0$ for all US states), such that $RS_s \times GDPR\_Enact_t$ and $RS_s \times GDPR\_Rollout_t$ are the interaction terms between the measure of regulatory strictness and the $GDPR\_Enact_t$ and $GDPR\_Rollout_t$ dummies.

[30] Our aim is to test whether regulatory strictness is at least partially contributing to the results. The reason for also including GDP per capita is because the two are likely correlated.

Similarly, $GDP \times GDPR\_Enact_t$ and $GDP \times GDPR\_Rollout_t$ are the interaction terms between a state's GDP per capita and the $GDPR\_Enact_t$ and $GDPR\_Rollout_t$ dummies. $GDP \times EU_s \times GDPR\_Enact_t$ and $GDP \times EU_s \times GDPR\_Rollout_t$ are the three-way interaction terms of a state's GDP per capita, the EU dummy, and the $GDPR\_Enact_t$ and $GDPR\_Rollout_t$ dummies.[31]

4 Overall Effects of GDPR

We begin by examining how the number of deals for each state in each category changes from the pre to the post period of the enactment and rollout of GDPR. Table 3 reports the effects of GDPR on the aggregate number of deals. We focus on the marginal effects computed from the estimated coefficients of the Poisson specification. Our baseline model (Column 1 of Table 3) suggests a 26.1% decrease in the number of EU venture deals after the rollout of GDPR but no significant effect after its enactment.[32]

We use RoW venture deals as an alternate control group. To do so, we contrasted the privacy laws of rest-of-the-world countries with GDPR. Despite the existence of a so-called 'GDPR Adequacy' measure,[33] a comparison of a country's data protection laws against GDPR is challenging because some countries (e.g., Israel) may meet adequacy during GDPR's enactment but have arguably weaker compliance due to smaller fines, while other countries (e.g., Japan) may meet adequacy at a later time but with arguably stricter enforcement. Consequently, we attempted different variations of the control and treatment group compositions of those RoW countries that meet adequacy; the results were similar throughout. The composition that we report is as follows: (i) Japan is part of the control with an interaction term between a dummy variable that equals 1 if the country is Japan and the month is May 2017 or later (when Japan enacted and rolled out a GDPR-like reg-

[31] Regulatory strictness RS_s only takes non-zero values for EU states, so three-way interactions $RS_s \times EU_s \times GDPR_t$ are the same as two-way interactions $RS_s \times GDPR_t$.

[32] The marginal effects in the Poisson specification are evaluated at the mean values of the covariates conditional on being in the EU.

[33] See, for example, `https://www.cnil.fr/en/data-protection-around-the-world`.

ulation"). (ii) Korea and Australia are part of the control group.[34] Israel is part of the control group despite meeting adequacy as its penalties for violations are small.[35] Canada is part of the control group despite "meeting adequacy for commercial organizations."[36] India, Russia, and China are part of the control group since they do not meet adequacy and have arguably weaker data protection environments. (iv) New Zealand, Uruguay and Argentina, each with relatively few observations and thus grouped into 'other countries,' do meet GDPR adequacy, although arguably with weaker regulations that will require adjustment to maintain adequacy;[37] we group them together with the remaining 'other countries' in the control group.[38]

Due to a wider variety of countries in the RoW group, our focus, in terms of categories, is on more-data related and less-data related ventures. This distinction may depend less on industry-country-specific regulations (e.g., some countries may have differing protections for health and finance-related data). We then proceed with a parallel empirical methodology using the newly defined treatment and control groups.

Column 2 of Table 3 indicates a 34.16% decrease in the monthly number of EU venture deals after the rollout of GDPR in comparison to their counterparts in RoW, but no significant effect after GDPR's enactment. An OLS specification with the dependent variable of $ln(1+\#$ of deals) in Columns 3 and 4 indicates a 18.17% and 27.31% decrease in the number of EU deals in comparison to the US and RoW, respectively, where the marginal effects on

[34]Australia has weaker laws than GDPR (e.g., `https://www.termsfeed.com/blog/gdpr-vs-australian-privacy-principles/`), and Korea is still vying for adequacy in the time frame of our sample.

[35]See, e.g., `https://www.timesofisrael.com/data-is-up-for-grabs-under-outdated-israeli-privacy-law-think-tank-says/`.

[36]The regulatory environment for data in Canada is still shifting, and is still arguably weaker than GDPR, with smaller penalties for violations (see, e.g., `https://www.jdsupra.com/legalnews/canada-to-update-data-law-to-gdpr-16052/`).

[37]See, e.g., `https://iapp.org/news/a/gdpr-matchup-new-zealands-privacy-act-1993/`.

[38]All other countries that meet adequacy, with the exception of European Economic Area (EEA) non-EU countries, are dropped in the initial data cleaning stage due to too few observations. Including or excluding them does not change the results. EEA non-EU countries (such as Norway, Switzerland, and Iceland) rolled out GDPR-like laws shortly after GDPR took effect—and the expectation was that they would do so. In the appendix, we present an alternate comparison where EEA countries are part of the treatment group along with the EU; the results are similar. As a robustness check, we tested a separate estimate using EEA countries as the treatment group; the results there also suggest that the rollout of GDPR has a negative and significant effect on the number of financing deals by EEA ventures in comparison to their US counterparts.

the number of deals are computed from the estimated coefficients of $EU \times GDPR\_Rollout$, accounting for the fact that the dependent variable is log of one plus the number of deals.

5 Heterogeneous Effects of GDPR

While the overall effects we measure may be negative and statistically significant for the rollout of GDPR, there may exist heterogeneity in the effects across different groupings of ventures. This section incorporates the measure of regulatory strictness delineated in Section 3, and then proceeds to apply the baseline specifications to different subsamples, where ventures are grouped by their propensities to use data, by business type (B2C or B2B), by their funding and development stages, and by their industry categories.

Table 4 reports the results that add regulatory strictness and GDP per capita interaction terms to the baseline specification. Column 1 suggests a 35.7% decrease in the number of EU venture deals after GDPR's rollout compared to US deals. The coefficients on the regulatory strictness and GDP per capita interaction terms are both significant and negative, suggesting that the negative effects of GDPR's rollout are larger in EU states that are richer or are expected to adopt stricter enforcement. Column 2 indicates a 36.24% decrease in the number of EU venture deals after GDPR's rollout relative to RoW deal, though both the regulatory strictness and the GDP per capita interaction terms are insignificant. OLS specifications with the dependent variable of $ln(1 + \#$ of deals) in Columns 3 and 4 indicate decreases of 10.56% and 21.86% in comparison to US and RoW deals, respectively, where the marginal effects on the number of deals are computed from the estimated coefficients of $EU \times GDPR\_Rollout$, accounting for the fact that the dependent variable is log of one plus the number of deals.

We report the marginal effects of GDPR's enactment and rollout for each subsample in Table 5.[39] Panels A and B report the results when using US and RoW deals as the control group, respectively. Columns 1 and 2 of Table 5 report the results from applying the

[39]The complete tables are reported in appendix tables A4-A7.

baseline number of deals specification, separately for each of two groups of venture deals, according to their likely propensity to use data. Consistent with the baseline results, Column 1 indicates that GDPR's rollout had negative effects on the number of deals by EU ventures in the more-data-related category, suggesting declines in the number of deals of 30.72% and 31.48% relative to US and RoW deals, respectively, but no significant effect from GDPR's enactment. For the group comprising less-data-related ventures, Column 2 suggests a smaller negative effect on the number of EU deals in comparison to their US counterparts, but no significant effect when compared to RoW deals. A seemingly unrelated regression (SUR) test indicates that the coefficients on $EU \times GDPR\_Rollout$ significantly differ across the more-data and less-data related venture groups, such that the more-data venture group is associated with larger negative effects following GDPR's rollout.

Column 3 of Table 5 indicates a significant negative effect of 4.21% from GDPR's enactment on the monthly number of B2C deals, and a decrease of 17.68% after GDPR's rollout, both in comparison to US deals, with a similar pattern when using RoW deals as the control group. B2B deals, in contrast, are only affected by the rollout of GDPR and in comparison to US deals, with a 10.81% decrease per Column 4. An application of a SUR test indicates that the coefficients across the two groupings differ, suggesting that B2C firms, which likely deal with a greater number of individual users—as opposed to a smaller number of customers in the form of businesses for B2B firms—are particularly susceptible to the effects from GDPR. This may be because the aspects of the regulation that focus most on individuals (e.g., opt in or legitimate interest, data management, and control, with potential fines per violation) are perceived as being more harmful to revenues, more likely to be enforced, and/or entail additional and potentially ongoing compliance costs.

Columns 5-7 of Table 5 report category-specific effects on the monthly number of deals for healthcare, financial, and information technology ventures. GDPR's enactment has insignificant effects and GDPR's rollout has significant negative effects across the three venture categories (although the healthcare and financial categories yield insignificant effects when using RoW deals as the control group). An application of a SUR test suggests that the negative effects of GDPR's rollout are significantly larger for information technology than for the healthcare or financial categories.

The somewhat smaller yet negative effects on ventures in the healthcare and financial categories versus other technology may be a consequence of more stringent safeguards across nations for health and finance-related data that predate GDPR. In the EU, for instance, Article 8 of the 1995 Data Protection Directive states that "Member States shall prohibit the processing of personal data revealing racial or ethnic origin, political opinions, religious or philosophical beliefs, trade-union membership, and the processing of data concerning health or sex life," which could limit the collection of healthcare data and financial data (e.g., if financial data can reveal information in the aforementioned prohibited categories) pre-GDPR.[40] In the US, the Health Insurance Portability and Accountability Act of 1996 (HIPAA) and the Gramm-Leach-Bliley Act (GLBA), for example, have mandated compliance for a number of years, though there are still substantial differences from GDPR (HIPAA, for instance, allows providers to require consent prior to providing services, a requirement that GDPR relaxes; GLBA, for instance, adopts an opt-out approach, where information is collected by default and consumers have a limited ability to opt out—GDPR, in contrast, mandates legitimate interest and/or informed opt-in consent for each type of data collected, and further requires data management, data auditing and classification, data risk identification and mitigation, and data interfaces for users to easily obtain their own data and request that it be deleted). GDPR also imposes substantially larger penalties of up to 4% of a firm's global revenues. While GDPR's effects are relatively smaller on EU ventures in the healthcare and financial categories in comparison to US ventures, the still substantial negative effects suggest that GDPR is widely transformational across the technology sector, even when compared to existing strict data regulations.

Additional examples of subsample heterogeneity are generated from four different venture

[40] https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:31995L0046&from=EN

age groups and three different funding stages, where we examine the effects of GDPR across these different groupings. Columns 8 and 9 of Table 5 indicate significant reductions in the number of monthly deals for ventures in the 0-3 and 3-6 year-old subsamples of 30.32% and 20.53% relative to their US counterparts, respectively. Columns 10 and 11 indicate significant reductions in the number of deals for ventures in the early and main funding stages of 34.01% and 20.05% relative to their US counterparts, respectively. Similar decreases are obtained when using RoW ventures as the control group, except for ventures in the 3-6 year-old grouping. An application of a SUR test suggests that the negative effects of GDPR's rollout are significantly larger for the youngest ventures and ventures in their early funding stages.

6 Robustness, Interpretation and Extensions

6.1 Cambridge Analytica

One may argue that heightened attention to privacy and other data rights in the EU—in general and/or due to GDPR's rollout, may entail that the Cambridge Analytica scandal, which first received widespread public attention in March 2018, may have a significantly greater impact on European markets than markets outside of the EU. In particular, one may argue that the drop in the average monthly number of EU venture deals, illustrated by Figure 1(a) at around the time of GDPR's rollout in May 2018, is influenced by or largely attributed to the Cambridge Analytica scandal, whether in connection with or independently of GDPR.

To rule out the Cambridge Analytica scandal as a potential explanation for the effects we detect, we construct a grouping that approximates 'social' ventures. To do so, we identify ventures associated with the keywords 'social,' 'social media,' and 'social entertainment' (either in their CB tags or in their VX business descriptions). We group ventures without those any of those keywords as 'non-social' types. Overall, 14.58% of deals are of the social type (of those, there are 11.17% deals with the 'social' tag, 5.12% with the 'social media' tag, and 3.78% with the 'social entertainment' tag, with overlaps).

We then use the social and non-social subsamples to run a difference-in-differences analysis to test the Cambridge Analytica effect on the number of social-type venture investment deals, using social-type deals as the treatment group and non-social-type deals as the control. We run the analysis in three different samples: US ventures, EU ventures, and RoW ventures. We use the pre-treatment period of January 2014 to March 2016 (same as our GDPR pre-treatment period, prior to GDPR's enactment), and the treatment period of April 2018 to April 2019 (approximately a year following the initial Cambridge Analytica revelations).

Table 6 reports the results. We find that the Cambridge Analytica event had a significant effect on social-type deals in all three samples, suggesting that, worldwide, ventures operating in closer proximity to the industry associated with the scandal secured fewer funding deals after its revelations. An application of a SUR test suggests that the effect is somewhat smaller in the EU relative to the US and RoW.

As an additional robustness check, we examine whether the effects we observe continue to hold when social-type deals are excluded from the sample. Table 7 reports the results from the main specification and the B2C vs. B2B comparison (the latter relative to US ventures) when excluding social-type deals, both of which are largely unchanged. Of note, the GDPR effect is somewhat more negative for B2C deals when excluding social-type deals. This can be explained by there being a more concentrated overlap between social-type and B2C deals (there are 29.57% social-type deals in the B2C subsample but only about 4.29% such deals in the B2B subsample), the timing of the effect being close to GDPR, and the Cambridge Analytica effect being somewhat larger for non-EU ventures.

6.2 Immediate and Short-Term Time Horizons

We have identified a significant effect from GDPR's enactment on B2C ventures, although the effect in the overall sample was insignificant. The post-enactment and pre-rollout period is approximately two years, and it is possible that the enactment effect on the overall sample is more pronounced as the rollout date is approached. To test for this possibility, we cut the post-enactment period into two time segments, one from April 2016 to March 2017 (post-enactment 1), and one from April 2017 to April 2018 (post-enactment 2). Columns 1 and 2 of Table 8 suggests that the 'post-enactment 2' period is associated with significant but relatively small negative effects of -1.32% and -2.08% on the monthly number of EU venture deals relative to their US and RoW counterparts, respectively.

There are multiple potential reasons for this negative effect. For instance, it could be that compliance costs need not be incurred in the first post-enactment year, but begin to show up on firms' financial statements in the second year. It could also be that some of the uncertainty surrounding compliance costs (e.g., in terms of potential guidelines or amendments from policymakers) is reduced in the second post-enactment year—this is evident in additional GDPR guidelines being released by the European Data Protection Board. While the negative impact from the second post-enactment year is relatively small, it is indicative of some action being taken by investors prior to GDPR's rollout. Although we cannot pinpoint the underlying reasons for this action, our B2C vs. B2B analysis suggests that the brunt of it is related to compliance from ventures that offer consumer-facing products. Since our estimates compare the post-enactment and post-rollout periods to the pre-enactment period, to the extent that there is an effect associated with the second post-enactment year, it provides a narrative of how the effects from GDPR on EU ventures develop over time.

The effects we have identified suggest a significant drop in the number of EU deals after GDPR's rollout. This may be because investors delay or altogether drop potential funding to ventures that they believe may not meet GDPR compliance, possibly due to challenges in achieving compliance rather than specific business models being less valuable (which may have been predicted prior to GDPR's rollout and/or led to a shorter-term reduction in funding). To test whether the effects we observe after GDPR's rollout extend over the post-rollout period, we segment the post-rollout period into two different 6-months sub-periods, and assess the effect of GDPR's rollout on the number of deals in each sub-period. Columns 3 and 4 of Table 8 suggest that the number of financing deals in the EU significantly decreases in both sub-periods, but more so in the sub-period immediately after the rollout of GDPR.[41] Figure 2 indeed suggests a larger drop in the number of deals immediately following GDPR's rollout and that a portion of the drop is sustained over time in our sample.

6.3 Interpretation

The different groupings we have considered thus far could be further nested with each other to offer a more granular level of analysis and shed light on the mechanism through which GDPR has influenced venture investment. Given the pre-enactment effects we observed for B2C deals and the stronger post-rollout effects on more-data-related ventures, we nested the B2C vs. B2B categorization in the more/less data-related subsamples, and then examined the effects of GDPR using the US and RoW as control groups.

The results are presented in Table 9, suggesting that B2C ventures that are more data related carry the brunt of the negative effects from GDPR, with a decrease in their number of deals of 14.53% and 15.89% after GDPR's enactment compared to their US and RoW counterparts, respectively, and 35.14% and 27.02% after its rollout. Specifically, Column 1 suggests that both GDPR's enactment and rollout have significant negative effects on the number of EU B2C deals in the more data-related subsample. B2B ventures in the more data-related subsample exhibit a significant negative effect only after GDPR's rollout, as Column 2 indicates, with the effect being smaller than for B2C ventures. Column 3 indicates that GDPR's rollout has a significant negative effect on the number of EU B2C deals in the less-data related subsample but no significant effect from GDPR's enactment. Both GDPR's enactment and rollout have no significant effect on the number of EU B2B deals in the less-data-related subsample. Panels A and B indicate that the all of the above results are similar when using US and RoW ventures as the control group. An application of a SUR test suggests that the negative effects from GDPR's rollout are significantly larger

[41] We run similar tests by subsample, combining the time dimension with industry category and the age group or funding stage of ventures; the results are in Table A3 in the appendix.

for more/less data related B2C ventures than for their B2B counterparts.

Of note, 52.8% of more-data related B2C deals in our sample are by 0-3 year old ventures and 27.4% are by 3-6 year old ventures. The results thus suggest negative and pronounced effects on ventures in the more-data related B2C category following both the enactment and rollout of GDPR, more than 80% of which are for newer, 0-6 year old ventures. Moreover, of deals completed by B2C ventures, 71.3% are by 0-6 year old ventures. Taken together along with the previous results, a picture emerges of a regulation that, at least in the short run, has primarily affected newer, consumer-facing, data reliant ventures, particularly in the period immediately after GDPR's rollout, though also before and after it.

At a high level, the reductions in deals we have identified indicate that for a large swathe of ventures, the negative effect on the number of deals takes place after GDPR's rollout, which may suggest longer-term reductions in profitability. At the same time, if a major platform on which some ventures rely releases substantively new policies for the purpose of compliance after GDPR's rollout, and those policies impact the business models of those ventures as well as their longer-term profitability, then both shorter-term costs pertaining to adjusting business models and longer-term reductions in profitability may result. Consequently, the interpretation of the post-rollout effects, while suggestive of longer-term reductions in profitability for some ventures, may not cleanly lend itself to bucketing costs into short-term vs long-term. Moreover, the larger effect in the initial 6 months post-rollout period may suggest that both are at play. A subset of ventures (more data related B2C ventures) exhibit significant effects after both GDPR's enactment and rollout, which may suggest both costs related to adjusting business models to meet regulatory requirements and longer-term reductions in profitability.

While there are multiple potential reasons for the effects we find on newer and B2C ventures, we posit a few possible explanations. First, of the subsample of deals raised by 0-6 year old ventures that we can classify as either B2B or B2C in our sample, 74.5% are raised by B2C ventures. Hence, the distribution of deals by younger ventures is skewed towards

B2C, and B2C ventures are likely have more individual users. This may mean that these ventures are potentially more impacted by GDPR in terms of their need for and difficulty of meeting compliance, exposing them to the brunt of GDPR's effects. Second, the shift of capital towards meeting compliance adequacy for those ventures, percentage-wise, is likely to be the largest, which may reduce their financial runway, increase their capital burn rate, and lengthen their requisite time period for viability and profitability, all of which would make them less attractive investments. Third, younger B2C ventures may still need to reach critical mass in terms of their own data collection, an objective made more difficult by the regulation. Fourth, younger ventures may depend more on access to users through existing platforms, and many of these platforms implemented new policies at or around the time of GDPR's rollout.

6.4 Data Privacy and Security Ventures

While we have thus far identified negative effects on investment, GDPR may also boost investment in ventures that relate to privacy and security. Due to greater proximity and increased local demand, EU ventures in this category may exhibit a relative rise in investment, though such a boost need not be confined to EU ventures.

To that end, we grouped together deals for ventures that are associated with keywords such as 'privacy,' 'security,' and 'data security' into a separate category. Unfortunately, there is a relatively low number (4,435) of such deals—an insufficient amount to result in a significant effect in our specification. However, there are observable upticks in the time-series trends of the number of such venture deals in both the EU and US, as Figure 3 illustrates. Specifically, prior to GDPR's enactment, the average number of monthly deals for ventures in the data and security category is 15 in the EU (in total across member states), 20 in the US (in total across states), and 17 in the rest of the world (in total across countries). These averages increase by 47% in the EU, 45% in the US, and 41% in the rest of the world following GDPR's enactment, and further rise by 55% in the EU, 34% in the US, and 46%

in the rest of the world after GDPR's rollout. Thus, the number of deals for privacy and security ventures rise globally, but relative more so in the EU after GDPR.

7 Conclusion

We presented analyses of the short-term effects of GDPR on investment in technology ventures. We broke down those effects according to ventures' propensities to utilize data, to face consumers or businesses, by four venture age groups, by three funding stages, and by four industry categories. We found evidence suggesting negative and pronounced effects following the rollout of GDPR on the number of venture deals, particularly in the period immediately after GDPR's rollout, and particularly for newer, data-related, and consumer facing ventures.

It is important to emphasize that our dataset is not a complete universe of venture funding, but rather a partial snapshot of primarily venture capital and angel investments in technology ventures. As such, our results must be taken with a bit of caution, given that the effects we observe may be incomplete. At the same time, our findings indicate that it is exactly those nascent ventures that are in the process of transitioning from angel to venture capital that may be most impacted by GDPR. We also acknowledge that other factors could influence the venture investment market, including both observable (e.g., CCPA) and unobservable (e.g., immigration, money flow constraints).

Another caveat is that the impact estimated on EU ventures is relative to their US or rest-of-the-world counterparts. To the extent that capital flows freely across continents, it is unclear whether the reduced investment in the EU may have in tandem translated to additional support for non-EU ventures or that it reflects the reluctance by investors to invest anywhere. If it is the former, our estimates may have overestimated the effects of GDPR; if it is the latter, our estimates may be conservative as our sample does not include ventures that could serve EU residents but are based in other countries. There is ample opportunity for future work to examine the effect of GDPR on the composition (e.g., foreign vs domestic) of venture investment.

Our statistical framework also does not single out the UK or Brexit from the rest of the EU, because the UK is a member state and is bound by GDPR in our sample period. However, we control for state fixed effects (for each EU member state and each US state) in all regressions. We included linear time trends for the EU and US separately in our robustness checks, and we tested whether the effects we detect as far as GDPR's rollout kick in any time before May 2018—presumably if the expectation of Brexit were the driving factor for average venture investment in the EU as a whole, the effects would have been detected in prior months.[42]

While some of our analyses concern the amount of dollars invested in technology, they are not necessarily translatable into welfare implications. For instance, a reduction in investment dollars in technology ventures could benefit welfare if firms that are potentially harmful from a societal perspective do not come to fruition. Similarly, it could be that data regulation encourages new types of innovation down the road. Moreover, although our sample extends almost one year after the rollout of GDPR, we have no insight into whether investors are taking a wait-and-see approach nor do we know the outside options of affected firms, both of which are avenues for future research. The long-term impact of GDPR on the EU technology venture scene will become clearer in the years ahead.

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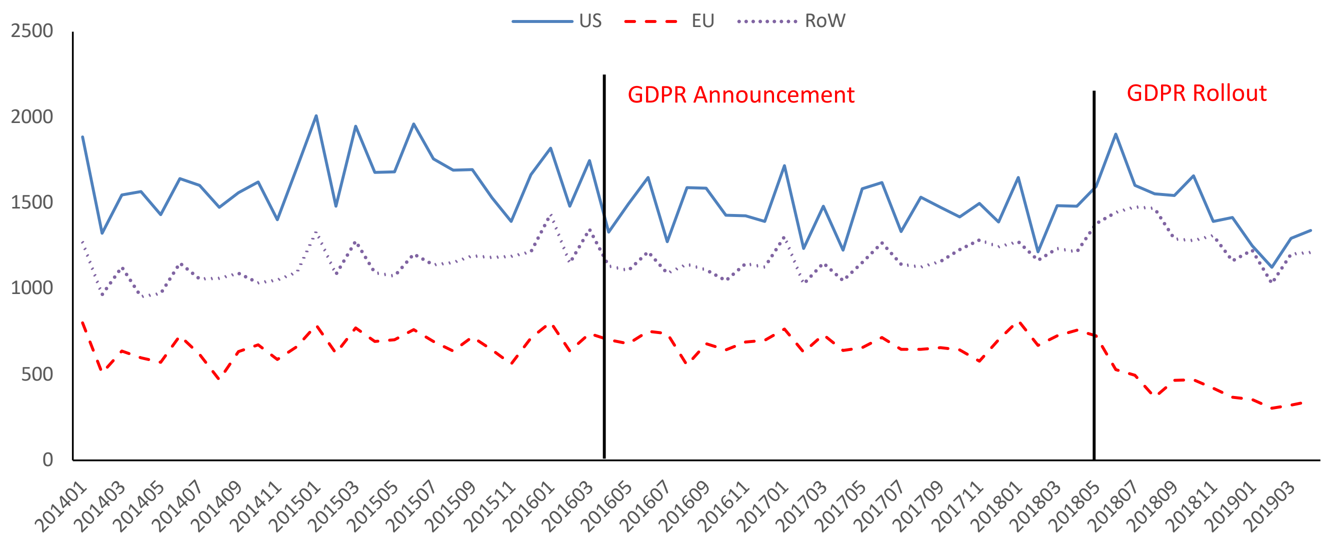
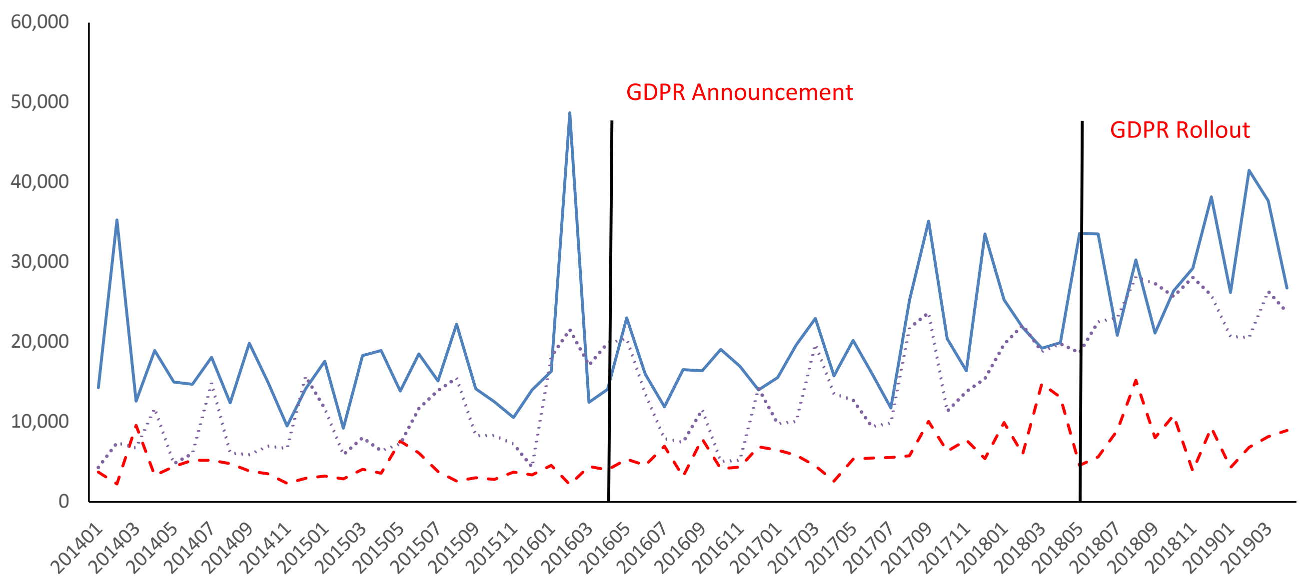
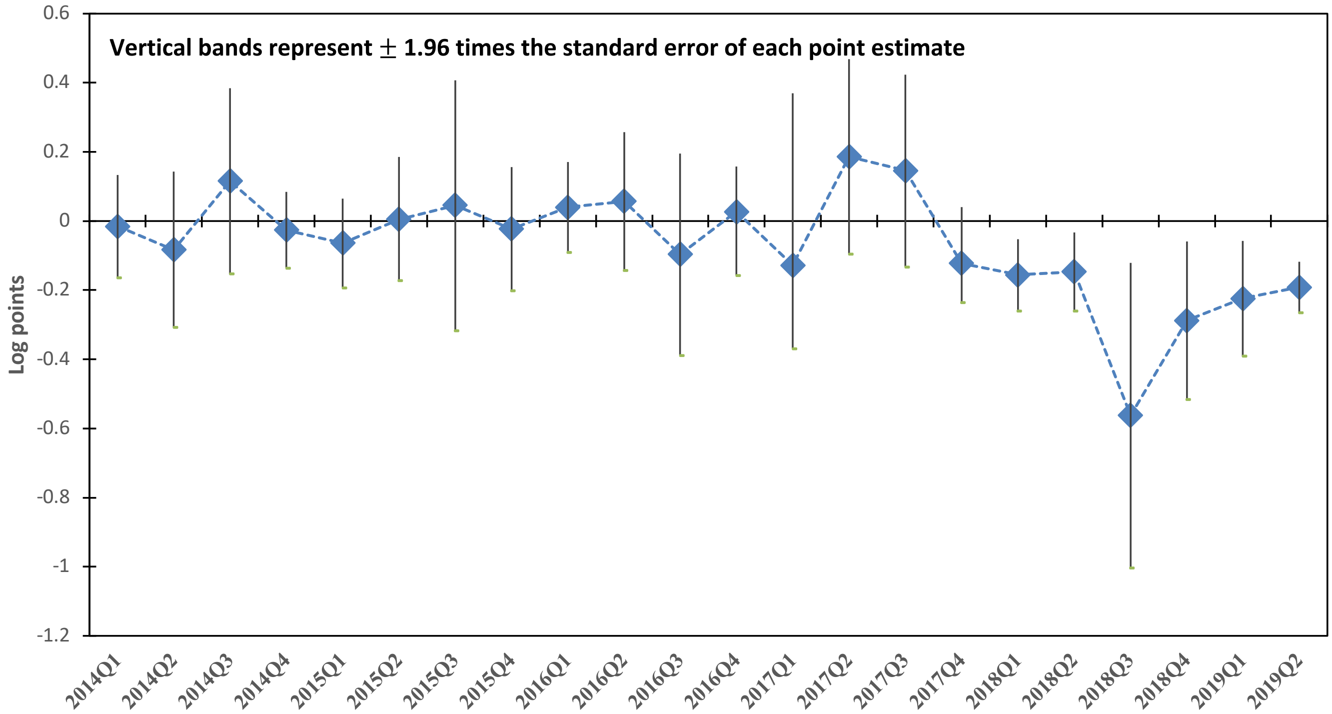


(a) Monthly # of deals in the EU, US, and RoW

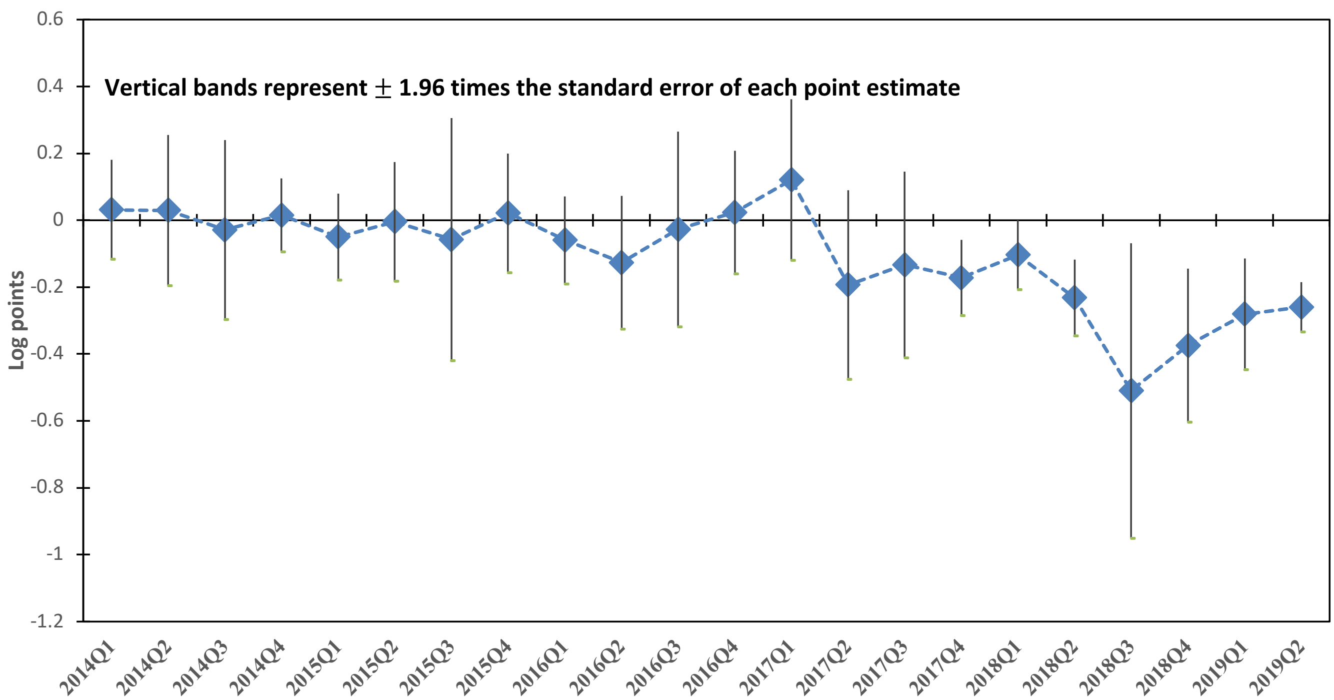


(b) Monthly $MM amount raised in the EU, US, and RoW

Figure 1. Aggregate monthly trend plots



(a) Number of deals between EU and US



(b) Number of deals between EU and RoW

Figure 2. Lead/lag effects of GDPR on aggregate # of deals on a quarterly basis – Poisson regression

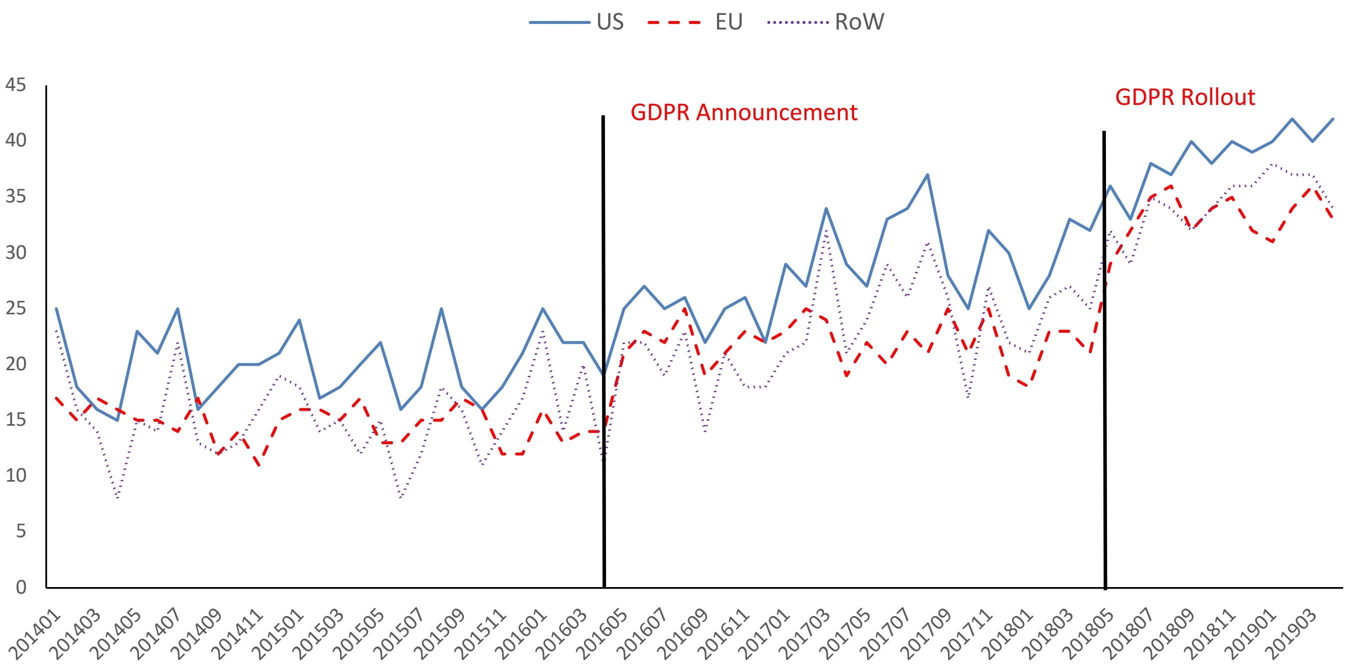


Figure 3. EU and US trends of the monthly # of privacy and security related deals

Table 1: Summary Statistics

	EU					US				
	Mean	Median	75%	95%	N	Mean	Median	75%	95%	N
Panel A: Whole Sample										
# of countries/states	-	-	-	-	24	-	-	-	-	51
# of months	-	-	-	-	65	-	-	-	-	65
# of categories	-	-	-	-	4	-	-	-	-	4
# of deals	6.62	2	7	30	6,144	7.58	2	6	26	13,056
$ MM amount raised per deal	11.15	0.96	3.50	29.48	29,779	22.18	2.19	9.47	60.01	67,717
Regulatory strictness	51.48%	53.55%	71.15%	81.85%	1,536	-	-	-	-	-
Unemployment	8.62%	7.1%	10.12%	20.72%	1,536	4.70%	4.60%	5.60%	6.90%	3,264
GDP per capita (in thousand)	35.21	-	-	-	1,536	57.15	-	-	-	3,264
CPI	108.51	108.37	110.35	113.85	1,536	111.16	110.21	113.46	115.83	3,264
Interest	-0.15%	-0.29%	0	0.29	1,536	0.72%	0.30%	1.25%	2.33%	3,264
Median Income (in thousand)	18.87	-	-	-	1,536	31.78	-	-	-	3,264
Stock Index	3,981	-	-	-	1,536	2,289	-	-	-	3,264
Firm age (exclude mature firm)	2.37	1.85	-	-	25,438	2.74	2.22	-	-	56,277
Firm age (whole sample)	4.49	2.24	-	-	29,779	5.46	2.77	-	-	67,717
Panel B: Subgroup by category										
Healthcare:										
# of deals	4.22	1	5	19	1,536	6.83	2	7	24	3,264
$ MM amount raised per deal	10.87	1.33	4.99	33.20	5,078	16.01	2.99	11.21	59.78	17,010
Financial:										
# of deals	2.94	1	3	12	1,536	2.73	1	2	8	3,264
$ MM amount raised per deal	16.56	1.41	5.82	52.72	3,386	26.95	2.80	12.71	100.00	6,453
Information Technology:										
# of deals	12.94	5	15	32	1,536	15.38	4	11	53	3,264
$ MM amount raised per deal	7.10	0.75	2.71	18.88	15,368	18.99	2.01	7.61	49.01	35,293
Others:										
# of deals	6.52	2	7	32	1,536	5.37	2	6	20	3,264
$ MM amount raised per deal	19.84	0.98	3.91	62.70	5,947	45.02	2.22	10.00	150.00	8,961
Panel C: Subgroup by venture business attribute										
More data-related										
# of deals	9.57	3.71	13.01	24.33	1,536	12.52	4.17	12.80	25.04	3,264
$ MM amount raised per deal	5.77	0.67	2.19	15.77	17,294	13.81	1.91	11.02	38.39	35,932
Less data-related										
# of deals	7.55	2.30	8	28	1,536	8.05	1.80	8.87	31	3,264
$ MM amount raised per deal	11.85	1.09	3.75	42.11	12,485	15.53	2.14	10.88	78.92	31,785
Business to Consumer (B2C)										
# of deals	6.05	3.15	10	22	1,536	8.22	3.95	12	29	3,264
$ MM amount raised per deal	3.47	0.56	1.92	12.76	8,446	4.15	1.05	2.56	14.19	15,568
Business to Business (B2B)										
# of deals	5.15	3	12	28	1,536	6.91	3.5	13	31	3,264
$ MM amount raised per deal	4.99	0.75	2.08	13.78	8,561	5.62	1.23	3.09	17.77	13,287

Table 1 Continued

	EU					US				
	Mean	Median	75%	95%	N	Mean	Median	75%	95%	N
Panel D: Subgroup by funding stage										
Early Stage:										
# of deals	16.14	6	15	60	1,536	12.86	1	4	38	3,264
$ MM amount raised per deal	1.40	0.33	1.07	3.95	17,961	3.25	0.61	2.00	10.01	30,966
Main Stage:										
# of deals	7.96	5	8	40	1,536	9.99	3	8	37	3,264
$ MM amount raised per deal	12.32	3.44	8.98	37.3	9,288	17.84	5.46	15.00	57.78	28,221
Late Stage:										
# of deals	5.84	1	5	37	1,536	6.81	3	8	26	3,264
$ MM amount raised per deal	74.78	10.66	42.00	287.14	2,530	103.99	12.56	50.00	367.00	8,530
Panel E: Subgroup by firm age										
New firm (0-3 year):										
# of deals	18.95	7	19	83	1,536	16.53	5	13	53	3,264
$ MM amount raised per deal	6.48	0.52	1.85	15.66	17,530	11.92	1.19	4.50	30.81	35,335
Young firm (3-6 year):										
# of deals	5.69	2	6	24	1,536	6.26	2	6	23	3,264
$ MM amount raised per deal	13.55	1.50	4.61	25.46	6,505	18.65	3.35	12.00	60.69	15,818
Established firm (6-9 year):										
# of deals	2.21	0	2	11	1,536	2.88	1	3	11	3,264
$ MM amount raised per deal	19.30	2.59	9.01	61.90	2,312	32.41	5.2	20.01	103.48	7,020
Mature firm (9+ year):										
# of deals	3.60	1	4	19	1,536	4.26	2	5	16	3,264
$ MM amount raised per deal	36.22	3.30	13.00	110.00	3,385	59.94	6.01	22.24	166.57	9,511

Note: The # of deals in each sub-group is per (member) state per month at the aggregate level. The $MM amount raised per deal is at the deal level.

Table 2: Summary Statistics –Rest of the World (RoW)

	RoW Major Countries					RoW Other Countries				
	Mean	Median	Std.ev	75%	N	Mean	Median	Std.ev	75%	N
Panel A: Whole Sample										
# of countries/states	-	-	-	-	12	-	-	-	-	47
# of months	-	-	-	-	65	-	-	-	-	65
# of categories	-	-	-	-	2	-	-	-	-	2
$ MM amount raised	576.86	393.72	615.90	718.29	1,536	22.85	13.51	30.05	25.58	5,504
# of deals	27.04	24.33	11.00	32.32	1,536	1.85	1.71	0.46	2.00	5,504
$/deal	12.65	8.26	51.10	10.86	32,148	11.66	7.70	64.69	11.75	19,867
Panel B: Subsample by different categories										
More data-related										
# of deals	10.68	5.60	9.89	16.32	1,536	13.22	5.03	12.42	14.02	5,504
Less data-related										
# of deals	7.62	2.58	6.36	8.58	1,536	9.68	3.76	8.87	10.47	5,504
Business to Consumer (B2C)										
# of deals	6.87	4.06	8.44	10.87	1,536	9.25	4.07	7.21	12.31	5,504
Business to Business (B2B)										
# of deals	6.29	3.63	5.12	13.60	1,536	7.91	4.09	4.08	14.26	5,504
Healthcare:										
# of deals	4.72	2.01	7.58	6.10	1,536	7.29	2.02	6.81	8.72	5,504
Financial:										
# of deals	4.54	2.81	5.29	3.89	1,536	4.09	1.66	5.09	2.08	5,504
Information Technology:										
# of deals	12.71	5.35	9.77	15.49	1,536	16.38	5.34	14.21	11.57	5,504
Early Stage:										
# of deals	17.91	7.87	10.04	16.30	1,536	13.99	2.88	9.70	5.26	5,504
Main Stage:										
# of deals	9.78	5.09	6.02	9.55	1,536	10.36	4.88	6.50	9.94	5,504
Late Stage:										
# of deals	6.73	1.32	3.21	5.68	1,536	7.36	3.17	3.01	9.12	5,504
New firm (0-3 year):										
# of deals	20.37	8.35	12.38	19.24	1,536	17.92	5.67	12.72	13.07	5,504
Young firm (3-6 year):										
# of deals	6.73	3.23	8.49	7.27	1,536	7.06	2.00	7.12	6.70	5,504
Established firm (6-9 year):										
# of deals	3.07	0.51	2.21	3.29	1,536	3.37	1.18	3.01	4.32	5,504
Mature firm (9+ year):										
# of deals	4.61	2.79	3.89	5.02	1,536	5.85	2.58	4.88	5.82	5,504

Note: RoW major contributing countries include Australia, Brazil, Canada, China, India, Israel, Japan, Mexico, South Korea, Russia, Singapore, and Switzerland. 'Other Countries' include 12 countries with total # of deals between 50 and 200, and 31 countries with total # of deals between 200 and 1000.

Table 3. GDPR impact on aggregate level # of deals

	(1)	(2)	(3)	(4)
	Baseline Poisson		OLS	
	EU vs US	EU vs RoW	EU vs US	EU vs RoW
GDPR_Enact	-0.043	-0.205	-0.201***	-0.258*
	(0.202)	(0.571)	(0.075)	(0.131)
EU * GDPR_Enact	0.063	0.067	0.084	0.128
	(0.074)	(0.155)	(0.060)	(0.211)
GDPR_Rollout	-0.284	-0.478	-0.481	-0.534*
	(0.261)	(0.335)	(0.578)	(0.274)
EU * GDPR_Rollout	-0.302***	-0.418**	-0.112**	-0.165*
	(0.108)	(0.213)	(0.054)	(0.077)
Marginal effect (rollout)	-26.1%**	-34.16%**	-18.17%**	-27.31%**
Macroeconomic variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Observations	19,200	8,850	19,200	8,850
R-squared	-	-	0.805	0.501
F-test on pre-treatment (p-value)	0.109	0.118	0.161	0.235

*Note: The dependent variable for Columns 1 and 2 is the # of deals per state per category per month, whereas it is ln (1+# of deals) for Columns 3 and 4. US venture deals are the control group in Column 1, whereas they are RoW deals in Column 2. Columns 1 and 2 report a Poisson specification, and Columns 3 and 4 report OLS with the same settings of Columns 1 and 2. The sample is composed of four different industry categories (healthcare, finance, information technology, and others) for EU vs US comparison but two different industry categories (more-data and less-data related) for the EU vs RoW comparison. Standard errors are clustered by state (i.e., member state in EU, state in US, and countries in RoW). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table 4. GDPR impact on aggregate level # of deals controlling for regulatory strictness

	(1)	(2)	(3)	(4)
	Baseline Poisson		OLS	
	EU vs US	EU vs RoW	EU vs US	EU vs RoW
GDPR_Enact	-0.021	-0.127	-0.181**	-0.310*
	(0.164)	(0.233)	(0.077)	(0.187)
EU * GDPR_Enact	0.027	0.095	0.020	0.093
	(0.153)	(0.138)	(0.080)	(0.166)
GDPR_Rollout	-0.341	-0.532	-0.495	-0.502*
	(0.210)	(0.324)	(0.341)	(0.255)
EU * GDPR_Rollout	-0.281**	-0.397*	-0.077*	-0.147**
	(0.135)	(0.215)	(0.043)	(0.072)
RegStri * GDPR_Enact	0.162	0.012	0.113	0.107
	(0.254)	(0.474)	(0.170)	(0.185)
RegStri * GDPR_Rollout	-0.145**	-0.138	-0.038**	-0.110
	(0.065)	(0.201)	(0.015)	(0.248)
GDP per capita * EU	0.007***	0.003	0.001	-0.035
	(0.003)	(0.014)	(0.002)	(0.174)
GDP per capita * GDPR_Enact	-0.001***	0.009	-0.000	0.012
	(0.000)	(0.047)	(0.000)	(0.033)
GDP per capita * GDPR_Rollout	-0.001	-0.023	-0.002	-0.042
	(0.002)	(0.088)	(0.0004)	(0.070)
GDP per capita * EU * GDPR_Enact	-0.002*	-0.129	-0.001	-0.185
	(0.001)	(0.111)	(0.001)	(0.326)
GDP per capita * EU * GDPR_Rollout	-0.005**	-0.179	-0.003**	-0.194
	(0.002)	(0.161)	(0.001)	(0.583)
Marginal effect (rollout)	-35.7%**	-36.24%*	-10.56%**	-21.86%**
Macroeconomic variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Observations	19,200	8,850	19,200	8,850
R-squared	-	-	0.805	0.444
F-test on pre-treatment (p-value)	0.134	0.153	0.105	0.211

*Note: The dependent variable in Columns 1 and 2 is the # of deals per state per category per month, whereas it is ln (1+# of deals) in Columns 3 and 4. US venture deals are the control group in Column 1 whereas it is RoW for Column 2. Columns 1 and 2 report a Poisson specification, and Columns 3 and 4 report OLS with the same settings of Columns 1 and 2. The sample is composed of four different industry categories (healthcare, finance, information technology, and others) for the EU vs US comparison but two different industry categories (more-data and less-data related) for the EU vs RoW comparison. Standard errors are clustered by state (i.e., member state in EU, state in US, and countries in RoW). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table 5. GDPR impact on # of deals across different subgroups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	More Data Related	Less Data Related	B2C	B2B	Healthcare	Financial	IT	New Firm (0-3 y.o.)	Young Firm (3-6 y.o.)	Early Stage	Main Stage
Panel A: EU vs US											
Marginal Effect (Enactment)	-	-	-4.21%**	-	-	-	-	-	-	-	-
Marginal Effect (Rollout)	-30.72%***	-15.47%*	-17.56%**	-10.77%**	-26.06%**	-21.33%**	-32.43%**	-30.32%***	-20.53%**	-34.01%***	-20.05%**
SUR Test on difference of GDPR rollout (p-value)	0.000		0.007		0.008	0.005		0.003		0.000	
Panel B: EU vs RoW											
Marginal Effect (Enactment)	-	-	-8.88%***	-	-	-	-	-	-	-	-
Marginal Effect (Rollout)	-31.48%**	-	-21.49%***	-	-	-	-15.83%*	-26.58%***	-	-35.50%***	-21.57%**
SUR Test on difference of GDPR rollout (p-value)	0.000		0.000		0.000	0.000		0.000		0.005	

*Note: Venture deals in the US are used as the control group in Panel A, whereas it is RoW deals in Panel B. For each subgroup, only report the marginal effects of GDPR's enactment and rollout are reported along with a corresponding SUR test for the difference in the coefficients of EU*GDPR rollout. The complete results are in the appendix. The SUR p-value of the difference between the coefficients of EU * GDPR_Rollout of the more-data-related and less-data-related groups is reported in the middle of Columns 1 and 2. The SUR test for the B2C and B2B comparison is in the middle of Columns 3 and 4. The SUR test for the healthcare/finance vs information technology comparison is in Columns 5 and 6. The SUR test for new and young firms is in the middle of Columns 8 and 9. The SUR test for the early and main stages is in the middle of Columns 10 and 11. We did not report the results for mature and late-stage firms since they are insignificant. Standard errors are clustered by state (i.e., member state in EU, state in US, and countries in RoW). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table 6. The effect of Cambridge Analytica on the number of social-type venture deals

	(1)	(2)	(3)
	US-only	EU-only	RoW-only
Post_CambridgeAnalytica	0.025	0.028	0.038
	(0.030)	(0.022)	(0.054)
Social-type * Post_CambridgeAnalytica	-0.096**	-0.058**	-0.067**
	(0.046)	(0.026)	(0.032)
Marginal effect (CambridgeAnalytica)	-9.15%**	-5.64**	-6.48%**
SUR test on difference of Social-type*Post_CambridgeAnalytica (US vs EU)	0.028		
SUR test on difference of Social-type*Post_CambridgeAnalytica (EU vs RoW)		0.019	
Macroeconomic variables	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	5,504	2,816	8,170

*Note: The dependent variable is # of deals per state per month. Column 1 corresponds to the sample containing only US venture deals, Column 2 corresponds to EU deals, and Column 3 corresponds to RoW deals. The SUR test p-value of the difference in the coefficients of Social-type * Post_CambridgeAnalytica between EU and US is reported in the middle of Columns 1 and 2, and similarly for EU and RoW in the middle of Columns 2 and 3. Standard errors are clustered by state (i.e., member state in EU, state in US, and countries in RoW). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table 7. GDPR impact on the number of non-social-type venture deals

	(1)	(2)	(3)	(4)
	Baseline Poisson			
	Whole Sample: EU vs US	Whole Sample: EU vs RoW	B2C: EU vs US	B2B: EU vs US
GDPR_Enact	-0.068	-0.069	-0.022	0.038
	(0.135)	(0.055)	(0.027)	(0.024)
EU * GDPR_Enact	0.071	0.124	-0.045**	0.023
	(0.066)	(0.101)	(0.017)	(0.363)
GDPR_Rollout	-0.218	-0.238	-0.112	-0.192
	(0.194)	(0.219)	(0.108)	(0.158)
EU * GDPR_Rollout	-0.319***	-0.468***	-0.228**	-0.108**
	(0.129)	(0.192)	(0.079)	(0.051)
Marginal effect (enactment)	-	-	-4.40%**	-
Marginal effect (rollout)	-27.31%***	-37.37%***	-20.39%**	-10.24%**
Macroeconomic variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	19,200	8,850	49,00	4,900

*Note: The dependent variable for Columns 1 and 2 is the # of deals per state per category per month, whereas it is # of B2C and B2B deals for Columns 3 and 4. US venture deals are the control group in Column 1, whereas they are RoW deals in Column 2. The sample is composed of four different industry categories (healthcare, finance, information technology, and others) for EU vs US comparison in Column 1 but two different industry categories (more-data and less-data related) for the EU vs RoW comparison in Column 2. Standard errors are clustered by state (i.e., member state in EU, state in US, and countries in RoW). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table 8. GDPR impact on the number of deals using separate post periods

	(1)	(2)	(3)	(4)
	Baseline Poisson			
	Whole Sample: EU vs US	Whole Sample: EU vs RoW	Whole Sample: EU vs US	Whole Sample: EU vs RoW
GDPR_Enact	-0.067	-0.026	-0.379	-0.218
	(0.172)	(0.245)	(0.694)	(0.234)
EU * GDPR_Enact-period1	0.052	0.064		
	(0.087)	(0.098)		
EU * GDPR_Enact-period2	-0.014**	-0.021**		
	(0.006)	(0.009)		
EU * GDPR_Enact			-0.255	-0.122
			(0.288)	(0.167)
GDPR_Rollout			-0.209	-0.328
			(0.365)	(0.423)
EU * GDPR_Rollout-period1			-0.418**	-0.497***
			(0.213)	(0.215)
EU * GDPR_Rollout-period2			-0.219**	-0.330***
			(0.102)	(0.144)
Marginal effect (enactment-period2)	-1.32%**	-2.08%**	-	-
Marginal effect (rollout-period1)	-	-	-34.15%**	-37.16%**
Marginal effect (rollout-period2)	-	-	-19.67%**	-28.11%**
Macroeconomic variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	13,730	7,320	19,200	8,850

*Note: The dependent variable is number of venture deals per state per month per category. Columns 1 and 2 report the effect of GDPR on the number of deals when separating the time periods in between post-enactment and pre-rollout into two equal sub-periods. Columns 3 and 4 report the effect of GDPR when similarly separating the post-rollout period into two 6-month sub-periods. Standard errors are clustered by state (i.e., member state in EU, state in US, and countries in RoW). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table 9. GDPR impact on the number of deals in B2C/B2B by data propensity

	(1)	(2)	(3)	(4)
	Baseline Poisson			
	B2C & More Data-related	B2B & More Data-related	B2C & Less Data-related	B2B & Less Data-related
Panel A: EU vs US				
GDPR_Enact	-0.247	-0.083	-0.323	-0.329
	(0.451)	(0.281)	(0.502)	(0.296)
EU * GDPR_Enact	-0.157**	-0.198	-0.138	-0.192
	(0.072)	(0.263)	(0.446)	(0.242)
GDPR_Rollout	-0.063	-0.227	-0.143	-0.185
	(0.351)	(0.325)	(0.195)	(0.271)
EU * GDPR_Rollout	-0.433***	-0.202*	-0.153**	-0.102
	(0.090)	(0.128)	(0.074)	(0.129)
Marginal effect (enactment)	-14.53%**	-	-	-
Marginal effect (rollout)	-35.14%***	-18.29%*	-14.19%**	-
SUR Test on difference of GDPR rollout (p-value)	0.000		0.001	
Macroeconomic variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	4,050	4,050	4,050	4,050
Panel B: EU vs RoW				
GDPR_Enact	-0.105	-0.241	-0.389	-0.431
	(0.273)	(0.283)	(0.320)	(0.387)
EU * GDPR_Enact	-0.173**	-0.367	-0.272	-0.306
	(0.085)	(0.242)	(0.490)	(0.253)
GDPR_Rollout	-0.328	-0.015	-0.286	-0.254
	(0.293)	(0.379)	(0.258)	(0.693)
EU * GDPR_Rollout	-0.315***	-0.172*	-0.133**	-0.094
	(0.106)	(0.096)	(0.061)	(0.193)
Marginal effect (enactment)	-15.89%**	-	-	-
Marginal effect (rollout)	-27.02%**	-15.80%*	-12.45%**	-
SUR Test on difference of GDPR rollout (p-value)	0.003		0.000	
Macroeconomic variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	3,380	3,380	3,380	3,380

*Note: The dependent variable is the number of venture deals per state per month per nested industry category (i.e., B2B/B2C & more/less data-related). US deals are the control group in Panel A, whereas it is RoW deals in Panel B. Columns 1 and 2 report the effect of GDPR on the number of more data-related B2C/B2B deals. Columns 3 and 4 report the effect of GDPR on the number of less data-related B2C/B2B deals. Standard errors are clustered by state (i.e., member state in EU, state in US, and countries in RoW). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

A Appendix

A.1 Effect on Aggregate Investment

The preceding analyses focus on the effects of GDPR on the number of financing deals per month-state-category, representing one component (an extensive margin) of venture investment. To get a more complete picture and as a robustness check, we test the effects of GDPR on both the total dollar amount raised per month-state-category (an overall metric) and the amount raised per deal conditional on having reached a deal (an intensive margin). For brevity, we restrict attention to US ventures as the control group, with similar results for RoW ventures.

We apply a Tobit specification censored at 0 to test the effect of GDPR on the total dollar amount raised per month-state-category. The regression equation is analogous to (1), with only the dependent variable differing. We use this specification because we only observe deals that in fact go through. Column 1 of Table A1 reports the results of our baseline Tobit specification. Similar to the number-of-deals specification, Column 1 suggests that GDPR's enactment had no significant effect on the monthly total dollar amount per EU state per category. However, each category (healthcare, finance, information technology) in each EU state experienced a \$7.91 (13.47%) million decrease in its average monthly per-state total after the rollout of GDPR (where the $EU \times GDPR\_Rollout$ coefficient is translated to a marginal effect that is evaluated at the mean value of the other covariates conditional on being in the EU, giving the impact due to being subject to GDPR; the bracketed percentage is calculated by dividing the marginal effect by the respective conditional sample average in each specification, accounting for whether the dollar amount is right censored). In Column 2, the monthly total dollar amount is right censored (winsorized) at the 95-percentile value (\$339 million) to reduce the influence of outliers; Column 2 suggests that each category, after top coding, incurs a \$3.56 (12.58%) million monthly decrease per EU state after the rollout of GDPR.

Column 3 adds in the measure of regulatory strictness, suggesting a \$4.55 (16.10%) million decrease in the total dollar amount per state per category after the rollout of GDPR. The coefficient on the regulatory strictness variable is significant and negative, indicating that greater perceptions of stricter enforcement are associated with a more negative effect of GDPR. In alternate specifications (linear median and 75% quantile regressions, in lieu of top-coded Tobit), we look at the impact of 0 censoring and fat tail at the aggregate level. Column 5 indicates that the total monthly dollar amount per state-category incurs a \$1.32 (11.06%) million decrease after the rollout of GDPR. The marginal effects are similarly computed using the estimated coefficient of $EU \times GDPR\_Rollout$, evaluating the covariates at their means conditional on being in the EU. Columns 6 and 7 report OLS log specifications, both indicating significant negative effects from GDPR's rollout on the total monthly amount.

A.2 Effect on Deal Size

At the deal level, we use the log of the amount raised per deal because the amount is always positive but its distribution is highly skewed. As a robustness check, we also report results that top-code the amount raised at the 95 percentile of the sample, as well as those from a median linear regression. Our baseline deal-level specification is given by:

$$ln(y_{jsct}) = \alpha_s + \alpha_c + \alpha_t + \delta X_{jsct} + \beta_1 EU_s \times GDPR\_Enact_t + \beta_2 EU_s \times GDPR\_Rollout_t + \varepsilon_{sct}, \quad (3)$$

where j identifies deals according to their assigned unique identifier, the dependent variable $ln(y_{jsct})$ is log of the dollar amount raised in deal j, α_t, α_s, and α_c are month, state and category fixed effects, X_{jsct} denotes deal-level variables such as funding type, investor type, and firm age, ε_{jsct} is an error term, and all other dummy variables are the same as previously.

Table A2 reports the results. Our baseline model in Column 1 suggests a 33.8% decrease in the amount per deal after the rollout of GDPR and no significant effect from GDPR's enactment. Column 2 reports a similar estimation when right-censoring the sample at the

95-percentile level, suggesting a similar reduction of 31.5%. Columns 3 and 4 report results from median and 75-percent quantile linear specifications, with similar outcomes.

A.3 Heterogeneous Effects with Separate Post-GDPR Periods

In Section 6.2, we separated the post-rollout period into two separate 6-months sub-periods, and reported the results in Table 8. Here, we also do so for some of the subsamples we have considered, combining the time dimension with industry category and the age group or funding stage of ventures. Table A3 reports the results, indicating larger drops in the number of monthly financing deals in B2C, more-data related, new (0-3 year old ventures), and in the early funding stage in the 6-month period after the rollout of GDPR. The results are similar with RoW ventures as the control group.

Table A1. GDPR impact on the aggregate monthly $ amount raised – EU vs US

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable: Aggregate $ amount					ln (1+$ amount)	
	Baseline Tobit Regression	Baseline Tobit with top-coded	Baseline Tobit with top-coded	Median Linear Regression	75% Quantile Linear Regression	OLS	OLS
Sample mean (in million)	58.70	28.25	28.25	-	11.93	-	-
GDPR_Enact	-47.097	9.619	2.138	-0.162	-0.995	-0.318	-0.603***
	(70.778)	(15.767)	(15.210)	(0.260)	(0.781)	(0.247)	(0.109)
EU * GDPR_Enact	42.559	7.829	13.155	-0.292	-2.116	-0.063	-0.110
	(27.395)	(5.303)	(9.387)	(0.532)	(1.706)	(0.116)	(0.115)
GDPR_Rollout	-13.047	-7.175	-28.480	-0.935	-3.622	-0.141	-0.239
	(90.938)	(20.957)	(20.763)	(0.633)	(5.283)	(0.196)	(0.303)
EU * GDPR_Rollout	-21.345*	-9.321**	-21.455**	-0.927	-1.573**	-0.136**	-0.125**
	(11.245)	(4.452)	(10.741)	(1.273)	(0.655)	(0.068)	(0.052)
RegStri * GDPR_Enact			-13.913	0.309	2.425		0.214
			(17.705)	(0.725)	(2.591)		(0.136)
RegStri * GDPR_Rollout			-55.741*	2.231	-2.402*		0.083
			(29.529)	(1.852)	(1.332)		(0.103)
GDP per capita * EU			-1.517*	-0.528	-1.881**		0.015
			(.842)	(0.440)	(0.778)		(0.012)
GDP per capita * GDPR_Enact			0.050	0.118	-0.023		0.029
			(0.033)	(0.188)	(0.619)		(0.018)
GDP per capita * GDPR_Rollout			0.317	0.953**	0.415		-0.002
			(0.287)	(0.375)	(0.792)		(0.029)
GDP per capita * EU * GDPR_Enact			0.194	0.748	0.355***		0.073
			(0.127)	(0.877)	(0.116)		(0.106)
GDP per capita * EU * GDPR_Rollout			0.471	0.226*	0.2218		0.098
			(0.377)	(0.129)	(0.732)		(0.112)
Marginal effect (rollout)	-7.91*	-3.56***	-4.55***	-	-1.32***	-13.6%**	-15.6%**
Marginal effect in percentage (rollout)	-13.47%	-12.58%	-16.10%	-	-11.06%	-	-
Macroeconomic variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,200	19,200	19,200	19,200	19,200	4,900	4,900
R-squared	-	-	-	0.423	0.425	0.551	0.683
F-test on pre-treatment (p-value)	0.203	0.133	0.109	-	-	-	-

*Note: The dependent variable is $MM amount raised per state per category per month. Column 1 repots the Tobit regression, Column 2 reports the Tobit regression with top-coding at the 95 percentile ($339 million), Column 3 adds a measure of regulatory strictness, and Columns 4 and 5 are quantile linear regressions. The sample is composed of four different industry categories (healthcare, finance, information technology, and others). Standard errors are clustered by state (i.e., member state in EU and state in US). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table A2. GDPR impact on $ amount raised per deal – EU vs US

	(1)	(2)	(3)	(4)
	Dependent variable: ln ($ amount per deal)			
	Baseline OLS	Baseline with top-coded	Median regression	75% quantile regression
GDPR_Enact	0.689***	0.690***	0.914***	1.036***
	(0.146)	(0.141)	(0.184)	(0.214)
EU * GDPR_Enact	-0.021	0.025	0.086	0.017
	(0.039)	(0.123)	(0.065)	(0.048)
GDPR_Rollout	1.726***	1.727***	2.049***	2.321***
	(0.192)	(0.188)	(0.215)	(0.233)
EU * GDPR_Rollout	-0.338***	-0.315***	-0.617***	-0.385***
	(0.065)	(0.137)	(0.099)	(0.102)
Marginal Effect (Rollout)	-33.81%***	-31.48%***	-61.67%***	-38.54%***
Macroeconomic variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	97,496	97,496	97,496	97,496
R-squared	0.497	0.502	0.224	0.222

*Note: The dependent variable is ln($MM raised per deal). Column 1 reports OLS, Column 2 reports OLS with top-coding at the 95 percentile ($75 million), Column 3 reports median linear regression, and Column 4 reports quantile linear regression at the 75 percentile. The sample is composed of four different industry categories (healthcare, finance, information technology, and others). Standard errors are clustered by state (i.e., member state in EU and state in US). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table A3. GDPR impact on the # of deals for different subgroups with separate post-GDPR periods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	B2C	B2B	More Data Related	Less Data Related	New Firm (0-3 y.o.)	Young Firm (3-6 y.o.)	Mature Firm (9+ y.o.)	Early Stage	Main Stage	Late Stage
Panel A: EU vs US										
GDPR_Enact	-0.095	-0.085	-0.145	-0.279	-0.695	-0.046	-0.009	-0.182	-0.307	-0.357
	(0.089)	(0.065)	(0.938)	(0.170)	(0.470)	(0.028)	(0.008)	(0.416)	(0.161)	-0.324
EU * GDPR_Enact	-0.074**	0.003	-0.128	0.062	-0.041	-0.032	0.042	0.069	0.011	0.019
	(0.031)	0.002	(0.482)	(0.046)	(0.008)	(0.025)	(0.017)	0.065	0.008	0.013
GDPR_Rollout	-0.156	-0.524	-0.202	0.482	-0.809	-0.427	-0.341	-0.941	-0.843	-0.784
	(0.125)	(0.360)	(0.180)	0.397	(0.766)	(0.343)	(0.247)	(0.759)	(0.569)	(0.543)
EU * GDPR_Rollout1	-0.322***	-0.133**	-0.576***	-0.179**	-0.397***	-0.269**	-0.232	-0.462***	-0.273**	0.108
	(0.124)	(0.067)	(0.127)	(0.078)	(0.181)	(0.120)	(0.401)	(0.201)	(0.137)	(0.113)
EU * GDPR_Rollout2	-0.141**	-0.094**	-0.221***	-0.136**	-0.283***	-0.157**	-0.185	-0.318**	-0.187**	0.078
	(0.071)	(0.040)	(0.084)	(0.065)	(0.131)	(0.060)	(0.162)	(0.162)	(0.082)	(0.129)
Marginal Effect (RolloutPeriod1)	-27.53%***	-12.47%**	-43.79%***	-16.39%**	-32.77%**	-23.59%**	-	-36.40%***	-23.89%**	-
Marginal Effect (RolloutPeriod2)	-13.15%**	-8.98%*	-19.82%***	-12.72%**	-24.65%**	-14.53%**		-27.24%***	-17.06%**	
Macroeconomic variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,900	4,900	4,900	4,900	4,900	4,900	4,900	4,900	4,900	4,900
Panel B: EU vs RoW										
GDPR_Enact	-0.242	-0.387	-0.215	-0.365	-0.032	-0.005	0.035	-0.747	-0.882	-0.341
	(0.160)	(0.227)	(0.201)	(0.194)	(0.019)	(0.005)	(0.022)	(0.413)	(0.635)	(0.257)
EU * GDPR_Enact	-0.102**	-0.242	-0.221	-0.131	-0.261	-0.374	-0.13	-0.502	-0.032	0.062
	(0.052)	(0.181)	(0.158)	(0.125)	(0.187)	(0.290)	(0.107)	(0.426)	(0.028)	(0.054)
GDPR_Rollout	-0.314	-0.306	-0.362	-0.153	-0.55	-0.462	-0.353	-0.768	-0.837	-0.721
	(0.247)	(0.262)	(0.300)	(0.108)	(0.372)	(0.450)	(0.236)	(0.536)	(0.807)	(0.687)
EU * GDPR_Rollout1	-0.278**	-0.162**	-0.466***	-0.352	-0.374***	-0.262*	-0.226	-0.485***	-0.274**	0.071
	(0.137)	(0.067)	(0.161)	(0.255)	(0.147)	(0.156)	(0.233)	(0.163)	(0.142)	(0.082)
EU * GDPR_Rollout2	-0.218**	-0.086*	-0.293*	-0.216	-0.244**	-0.207	-0.207	-0.315*	-0.212*	0.114
	(0.097)	(0.048)	(0.158)	(0.294)	(0.122)	(0.156)	(0.281)	(0.163)	(0.131)	(0.116)
Marginal Effect (RolloutPeriod1)	-24.27%**	-14.97%**	-37.25%***	-	-31.20%***	-23.05%*	-	-38.43%***	-23.97%**	-
Marginal Effect (RolloutPeriod2)	-19.59%**	-8.41%*	-25.40%***	-	-21.65%**	-	-	-27.02%*	-19.10%**	-
Macroeconomic variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,050	4,050	4,050	4,050	4,050	4,050	4,050	4,050	4,050	4,050

*Note: The dependent variable is the number of venture deals per state per month per category. The post-rollout period is separated into two 6-month sub-periods. Standard errors are clustered by state (i.e., member state in EU, state in US, and countries in RoW). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table A4. GDPR impact on # of deals for different subgroups – EU vs US

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Poisson regression on # of deals		Poisson regression on # of deals		Poisson regression on # of deals		
	More Data Related	Less Data Related	B2C	B2B	Healthcare	Financial	IT
GDPR_Enact	-0.281	-0.204	-0.057	0.043	-0.316	0.281	0.077
	(0.200)	(0.274)	(0.494)	(0.209)	(0.254)	(0.201)	(0.248)
EU * GDPR_Enact	0.128	0.093	-0.043**	0.011	0.102	0.077	0.027
	(0.093)	(0.149)	(0.017)	(0.339)	(0.094)	(0.057)	(0.074)
GDPR_Rollout	-0.128	0.525	-0.155	-0.188	-0.570**	0.941**	-0.077
	(0.381)	(0.489)	(0.558)	(0.197)	(0.284)	(0.395)	(0.310)
EU * GDPR_Rollout	-0.367***	-0.168**	-0.193**	-0.114**	-0.302***	-0.240**	-0.392***
	(0.124)	(0.085)	(0.073)	(0.055)	(0.121)	(0.115)	(0.162)
Marginal Effect (Enactment)	-	-	-4.21%**	-	-	-	-
Marginal Effect (Rollout)	-30.72%***	-15.47%*	-17.56%**	-10.77%**	-26.06%**	-21.33%**	-32.43%***
SUR Test on difference of GDPR rollout (p-value)	0.000		0.007		0.008	0.005	
Macroeconomic variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,900	4,900	4,900	4,900	4,900	4,900	4,900

*Note: The dependent variable is # of deals in each subcategory. The control group is US ventures. The SUR test p-value of the difference between the coefficients on EU * GDPR_Rollout of the more-data-related and less-data-related groups is reported in the middle of Columns 1 and 2. The SUR test for B2C and B2B is reported in the middle of Column 3 and 4. The SUR test for healthcare/finance vs information technology is reported in Columns 5 and 6. Standard errors are clustered by state (i.e., member state in EU and state in US). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table A5. GDPR impact on # of deals for different subgroups – EU vs RoW

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Poisson regression on # of deals		Poisson regression on # of deals		Poisson regression on # of deals		
	More Data Related	Less Data Related	B2C	B2B	Healthcare	Financial	IT
GDPR_Enact	-0.133	-0.272	-0.144	-0.329	0.031	-0.445	0.066
	(0.590)	(0.354)	(0.263)	(0.267)	(0.661)	(0.336)	(0.149)
EU * GDPR_Enact	-0.153	-0.127	-0.093***	-0.194	-0.084	-0.135	-0.128
	(0.284)	(0.169)	(0.034)	(0.233)	(0.192)	(0.218)	(0.299)
GDPR_Rollout	-0.335	-0.101	-0.147	-0.093	-0.391	-0.376	0.037
	(0.380)	(0.338)	(0.298)	(0.397)	(0.410)	(0.430)	(0.345)
EU * GDPR_Rollout	-0.378**	-0.281	-0.242***	-0.142	-0.027	-0.068	-0.205*
	(0.185)	(0.247)	(0.090)	(0.111)	(0.240)	(0.246)	(0.110)
Marginal Effect (Enactment)	-	-	-8.88%***	-	-	-	-
Marginal Effect (Rollout)	-34.48%**	-	-21.49%***	-	-	-	-15.83%*
SUR Test on difference of GDPR rollout (p-value)	0.000		0.007		0.008	0.005	
Macroeconomic variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,050	4,050	4,050	4,050	4,050	4,050	4,050

*Note: The dependent variable is # of deals in each subcategory. The control group is RoW ventures. The SUR test p-value of the difference between the coefficients on EU * GDPR_Rollout of the more-data-related and less-data-related groups is reported in the middle of Columns 1 and 2. The SUR test for B2C and B2B is reported in the middle of Column 3 and 4. The SUR test for healthcare/finance vs information technology is reported in Columns 5 and 6. Standard errors are clustered by state (i.e., member state in EU and state in US). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*

Table A6. GDPR impact on # of deals by venture development stage – EU vs US

	(1)	(2)	(3)	(4)	(5)	(6)
	New Firm (0-3 y.o.)	Young Firm (3-6 y.o.)	Mature Firm (6-9 y.o.)	Early Stage	Main Stage	Late Stage
GDPR_Enact	-0.682***	0.013	0.044	-0.727***	-0.245*	-0.327***
	(0.079)	(0.128)	(0.214)	(0.121)	(0.141)	(0.118)
EU * GDPR_Enact	0.081	0.071	0.060	0.073	0.087	0.075
	(0.102)	(0.049)	(0.066)	(0.058)	(0.083)	(0.065)
GDPR_Rollout	-0.579	-0.395	-0.334	-0.627	-0.827	-0.712
	(0.431)	(0.280)	(0.301)	(0.592)	(0.684)	(0.447)
EU * GDPR_Rollout	-0.361***	-0.225**	-0.221	-0.415***	-0.223**	0.083
	(0.139)	(0.101)	(0.185)	(0.141)	(0.108)	(0.440)
Marginal effect (rollout)	-30.32%***	-20.53%**	-	-34.01%***	-20.05%**	-
SUR Test on difference of GDPR rollout (p-value)		0.003	0.000		0.000	0.000
Macroeconomic variables	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,900	4,900	4,900	4,900	4,900	4,900

*ote: The dependent variable is # of deals in each subcategory. The control group is US ventures. The SUR test p-value `the difference in the coefficients of EU * GDPR_Rollout of young/mature firms vs new firms is reported in Columns 2 ıd 3. The SUR test for main/late stage vs early stage financing is reported in Columns 5 and 6. Standard errors are ustered by state (i.e., member state in EU and state in US). ***, **, and * indicate significance at the 1%, 5%, and)% level.*

Table A7. GDPR impact on # of deals by venture development stage – EU vs RoW

	(1)	(2)	(3)	(4)	(5)	(6)
	New Firm (0-3 y.o.)	Young Firm (3-6 y.o.)	Mature Firm (6-9 y.o.)	Early Stage	Main Stage	Late Stage
GDPR_Enact	-0.068	-0.044	0.052	-0.068	-0.044	0.052
	(0.052)	(0.107)	(0.023)	(0.052)	(0.107)	(0.023)
EU * GDPR_Enact	-0.143	-0.173	-0.119	-0.143	-0.173	-0.119
	(0.190)	(0.291)	(0.107)	(0.190)	(0.291)	(0.107)
GDPR_Rollout	-0.537	-0.443	-0.338	-0.537	-0.443	-0.338
	(0.373)	(0.452)	(0.239)	(0.373)	(0.452)	(0.239)
EU * GDPR_Rollout	-0.309***	-0.235	-0.217	-0.309***	-0.235	-0.217
	(0.135)	(0.156)	(0.257)	(0.135)	(0.156)	(0.257)
Marginal effect (rollout)	-26.58%***	-	-	-35.50%***	-21.57%**	-
SUR Test on difference of GDPR rollout (p-value)		0.003	0.000		0.000	0.000
Macroeconomic variables	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,050	4,050	4,050	4,050	4,050	4,050

*Note: The dependent variable is # of deals in each subcategory. The control group is RoW ventures. The SUR test p-value of the difference in the coefficients of EU * GDPR_Rollout of young/mature firms vs new firms is reported in Columns 2 and 3. The SUR test for main/late stage vs early stage financing is reported in Columns 5 and 6. Standard errors are clustered by state (i.e., member state in EU and state in US). ***, **, and * indicate significance at the 1%, 5%, and 10% level.*

Table A8. GDPR impact on the aggregate # of deals – European Economic Area (EEA) vs US & RoW

	(1)	(2)	(3)	(4)
	EEA+EU vs US	EEA+EU vs RoW	EEA+EU vs US	EEA+EU vs RoW
	Baseline Poisson	Baseline Poisson	OLS	OLS
GDPR_Enact	-0.051	-0.319	-0.224***	-0.488***
	(0.211)	(0.220)	(0.066)	(0.121)
EU * GDPR_Enact	0.038	0.097	0.062	0.128
	(0.081)	(0.128)	(0.071)	(0.211)
GDPR_Rollout	-0.212	-0.478	-0.392	-0.792***
	(0.189)	(0.335)	(0.512)	(0.144)
EU * GDPR_Rollout	-0.328***	-0.445**	-0.125**	-0.183**
	(0.119)	(0.220)	(0.061)	(0.086)
Marginal effect (rollout)	-26.72%*	-35.91%**	-12.54%*	-19.39%**
Macroeconomic variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Observations	20,800	9,100	20,800	9,100
R-squared	-	-	0.818	0.562

*Note: The dependent variable in Columns 1 and 2 is the # of deals per state per category per month in a Poisson specification, whereas it is ln (1+# of deals) in Columns 3 and 4 in an OLS specification. The sample is composed of four different industry categories (healthcare, finance, information technology, and others) in the EU+EEA vs US comparisons and two different industry categories (more/less data-related) in the EU+EEA vs RoW comparison. Standard errors are clustered by state (i.e., member states in EU and EEA, states in US, and countries in RoW). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.*