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Big Tech platform acquisitions of start-ups and venture capital funding for innovation

Tiago S. Prado*, Johannes M. Bauer

Department of Media and Information, Quello Center for Media and Information Policy, Michigan State University, East Lansing, MI, USA

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ABSTRACT

This paper investigates the effects of "Big Tech" platform acquisitions on venture capital (VC) funding for start-ups. We analyze 32,367 venture capital deals between 2010 and 2020, and 392 tech start-up acquisitions by Google, Facebook, Amazon, Apple, and Microsoft. Results obtained with fixed effects panel and differences-in-differences estimators reveal a positive, statistically significant, average effect of Big Tech start-up acquisitions on worldwide, venture capital activity. Positive effects were also found for the United States and Europe. However, the findings suggest that the effects are transient and fade away after several quarters. Because venture capitalists fund start-ups to enable entrepreneurial innovation, this approach also informs our understanding of the repercussions of these acquisitions on the start-up innovation ecosystem. The large number of observations over an extended period unlocks insights into historical patterns that are relevant for the design of digital platform policies.

1. Introduction

This article examines the effects of acquisitions by "Big Tech" platforms, such as Google, Amazon, Apple, Facebook, and Microsoft, on venture capital funding to emerging companies. Big Techs regularly acquire promising start-up companies ("start-ups") in their early stages of development. The five U.S. Big Techs have collectively acquired more than 800 start-ups during the past decades (CB Insights, 2021). Recent investigations by antitrust authorities in the United States and Europe of past, Big Tech, start-up acquisitions have focused attention among scholars and practitioners on the effects of these transactions on competition and innovation (U.S. Federal Trade Commission, 2020; Motta and Peitz, 2021; Varian, 2021; Katz, 2021).

The policy debate is divided by contradictory assertions. One position emphasizes that Big Tech acquisitions of start-up companies directly and indirectly suppress entrepreneurship and stifle innovation. It is argued that such acquisitions contribute to the creation of "kill zones" by discouraging additional investment by venture capitalists (VCs) in lines of business with a strong presence of Big Tech firms (e.g., Schechter 2018; Smith 2018; McLeod 2020; Waters 2020). A contrasting position holds that Big Tech acquisitions serve a useful purpose, that many of them fail, and that they have contributed to growing venture investment overall (Byrne, 2018; Kennedy, 2020).

Discussions among venture capitalists, academics, and entrepreneurs provide a more differentiated picture. They suggest that start-up acquisition strategies employed by Big Techs may have ambiguous short- and long-run effects on innovation (U.S. Department of Justice, 2020). In the short term, Big Tech acquisitions may discourage VC investment in early-stage start-ups that aim at the same industry segments. Because large digital platforms are able to imitate innovations quickly, venture capitalists may shy away from investing in companies that directly compete with them. At the same time, the prospect of selling a start-up to Big Tech platforms offers an attractive exit strategy for VCs to recoup their investment. Other things being equal, this prospect likely boosts their investment in start-ups.

Similar ambiguous effects exist in a longer-term strategic perspective. Big Tech acquisitions may be a strategy to reduce the threat that new competitors might emerge and eventually chal-

* Corresponding author.
E-mail address: pradotia@msu.edu (T.S. Prado).

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lenge their own business. If acquisitions reduce potential competition, they may, therefore, reduce the innovation incentives among incumbent Big Techs. On the other hand, consumers might benefit from innovations created by early-stage start-ups that are scaled up and integrated by Big Techs into their digital platforms after the acquisition. The net effect of these opposite effects is difficult to discern theoretically and will have to be informed by empirical analyses. Based on a large dataset, our paper is a first step toward such an assessment.

Our work contributes to an emerging research literature that provides differentiated insights for several industries. The identified effects of acquisitions are typically contingent on specific market conditions (e.g., Letina et al. 2021; Fumagalli et al. 2020). However, very little available empirical work examines these concerns and the overall net outcome for information technology industries. Empirical work about the conditions under which undesirable outcomes might materialize and what could be done to mitigate them is also lacking. This paper seeks to narrow this gap by investigating one aspect of this discussion. We focus on the short-term effects of Big Tech acquisitions on venture capital funding for start-ups. In as far as venture capital funding serves to support entrepreneurial innovation, this empirical approach, detailed in Section four, also sheds light on the repercussions of Big Tech acquisitions on innovation.

For this purpose, we analyzed a large dataset of 32,367 venture capital deals and 392 tech start-up acquisitions made worldwide between 2010 and 2020 by Google, Facebook, Amazon, Apple, and Microsoft in 173 different segments of the tech economy. Controlling for other factors that may have an effect on VC activity, such as initial public offerings (IPOs) and other mergers and acquisitions (M&As), we employed two estimation methods to estimate the response of VC activity to Big Tech start-up acquisitions.

First, to examine the response of VC activity to an increased level of Big Tech acquisitions in a given industry segment, we employed a two-way fixed effects Poisson estimation with covariates (Wooldridge, 2010). Second, to assess whether these effects may be causally attributed to Big Tech acquisitions, we made use of an innovative dynamic differences-in-differences setup. Proposed by Imai et al. (2021), it allows staggered treatment effects and switching treatment status.

The two-way fixed effects estimation revealed that the global, total number of VC deals in an industry segment increased by 20.2% on average in the four quarters that followed an increase in the number of Big Tech start-up acquisitions. By constraining our analysis to acquisitions that targeted start-up companies based in the United States, we found an average increase of 21.1% in the total number of VC deals, and an average increase of 30.7% in the total amount of VC funding in the four quarters following an increase in the number of Big Tech start-up acquisitions. Similarly, VC funding for European-based start-ups increased by 130.6% on average.

When all acquisitions that happened in a given industry segment were considered, the difference-in-differences dynamic estimation setup revealed an average increase of 6.37% in the total number of VC deals worldwide in the quarter of an acquisition in the industry segment that received the acquisition. By exploring the average effects of only the first acquisition in each industry segment, we found a 12.17% increase in the number of VC deals in the quarter of the acquisition, followed by an increase of 17.88% and of 11.63% in the two subsequent quarters.

Examining the average effects of an acquisition on the amount of VC funding, we found an 18.92% increase in the quarter of the acquisition when we analyzed all of the acquisitions. When we considered only the very first acquisitions that happened in each industry segment, we found a 48.61% and 39.31% increase in the two quarters following the quarter of the acquisition. When we considered all Big Tech start-up acquisitions, we also found a statistically significant 13.32% and 15.26% increase in the average VC funding per deal per quarter in the quarter of an acquisition and in the first quarter after it, respectively. When we isolated the very first acquisitions, the average effects found were bigger - a 31.58% and 24.31% increase, respectively.

Analysis of the effects of Big Tech acquisitions of U.S.-based start-upsrevealed a 14.02% average increase in the number of VC deals in the first quarter after the very first acquisition per industry segment. In contrast, when all acquisitions were considered for deals targeting European-based start-ups, we found a 9.44% increase in the number of VC deals, a 33.97% increase in the total amount of VC funding, and a 28.82% increase in the average amount of VC funding per deal per quarter in the first quarter following the quarter of an acquisition.

Our work contributes to the research literature and current policy discussions. We demonstrate a feasible empirical strategy to assess the effects of Big Tech acquisitions on start-up funding. The results do not provide evidence of a negative short-term effect. They are compatible with suggestions that Big Tech acquisitions are one of the mechanisms that venture capitalists use to realize a return on investment. Making such acquisitions more difficult may result in less VC investment (e.g., Cabral 2021). These insights also inform current, competition, policy discussions and can help to provide factual grounding to pending proposals.

The remainder of this paper is organized as follows. Section two reviews the literature on the importance of VC investment for funding start-up innovation, the main drivers of VC investment, and the impact of Big Tech, start-up acquisitions on VC activity. Section three provides details of the dataset used in this research, and Section four outlines the empirical strategy employed in the study. Sections five and six present our estimation methods and discuss the main empirical findings. Section seven discusses some implications of our results for competition policy and the regulation of Big Tech start-up acquisitions. Section eight concludes the paper.

2. Venture capital and the funding of start-up innovation

Venture capital is defined as “equity or equity-linked investments in young, privately held companies, where the investor is a financial intermediary who is typically active as a director, an advisor, or even a manager of the firm” (Kortum and Lerner, 1998, p. 3). Venture capitalists’ investments are commonly preceded by angel and seed investments that support a firm during its very early development, including pre-operation, market research, product development, and small-scale, product launch phases (Gompers and Lerner, 2004). After a startup has stablished a consistent performance record, such as a growing user base, a positive cash-flow, and sales growth, it may seek more venture capital to support continued growth.

To mitigate risks, venture capitalists typically follow a staged, capital infusion mechanism (Gompers and Lerner, 2001). The first round of capital infusion to a firm is identified as a Series A investment. Subsequent rounds may occur and are classified as Series B, C, D and E. These rounds of capital infusion often have similar characteristics, because they are aimed at supporting the start-up to scale up and commercialize the innovation. Each new round adds capital from new or incumbent investors in exchange for equity in the firm. The management literature has identified this stage-financing approach and the active role played by venture capitalists on the boards of start-ups in their portfolios as important tools for the success of tech entrepreneurship (Da Rin et al., 2013). In this study, our main goal is to investigate whether and to what extent Big Tech start-up acquisitions affect this venture capital ecosystem, which provides vitally important support for innovation in the tech industry.

2.1. Venture capital and innovation

Our research considers the role of VC in providing funding to start-ups for purposes of innovation, broadly defined to include new products and services, new processes, new business models, and the expansion of markets (OECD, 2018). Innovation is difficult to measure directly. Consequently, proxies that measure inputs to the innovation process (e.g., R&D spending) or its outputs (e.g., patents) are typically used (OECD, 2018). Our approach focuses on a broad measure of inputs, namely resources available for entrepreneurial and innovation purposes. There is abundant evidence in the research literature of a close relationship between VC funding and measures of innovation activity, such as patents and research and development (R&D) spending. The direction of this relationship, however, is contested. On the one hand, VC investors are considered "company builders," who are committed to providing mentorship and capital to emerging entrepreneurs with innovative ideas that have the potential for commercial success (Lerner, 1995; Baker and Gompers, 2003). On the other hand, VC investors may be attracted to financing firms that already have a mature innovation strategy but need capital to scale up, grow, and promise a successful exit option for the venture capitalist in the short to medium term (Bottazzi and Da Rin, 2002).

Kortum and Lerner (2000) used an external shock on venture capital activity generated by the 1979 "prudent man" reform in pension fund rules, which increased venture capital funding in the United States. Their study identified a positive, causal impact of venture capital on rates of patenting. Faria and Barbosa (2014) similarly found robust evidence to support a positive, causal effect of venture capital activity on innovation. Between 2000 and 2009, they detected an endogenous, dynamic relationship between VC investment and patent filings observed in seventeen European countries. The authors concluded that this effect resulted from later-stage VC investments, although they provided no details about what they consider early and late-stage VC funding or the theoretical grounds for this finding.

Research by Da Rin and Penas (2007) investigated whether venture capital influences the way companies integrate new knowledge into the innovation process. The authors analyzed the absorptive capacity - "the capacity of a firm to assimilate and exploit new knowledge" - of a sample of nearly 8,000 Dutch firms from 1998 to 2004. Controlling for the selection process that compels venture capitalists to give preference to funding more innovative, promising companies, the authors found that venture capital affected a firm's innovation strategies by directing research and development (R&D) efforts more regularly toward "make" rather than "buy" activities.

A review article by Lerner and Nanda (2020) critically analyzed the state of knowledge about the role played by VC investment to foment innovation. Although the authors recognized the importance of the VC investments to spur innovation, as supported by previous literature, they discussed some limitations of this relationship. First, they argued that a very narrow band of technological innovations fits the requirements of VC investors. These are primarily innovations with a short-term prospect for commercialization. However, such innovations frequently bring limited societal benefits.

Second, Lerner and Nanda claimed that VC investors with deep pockets have a great influence on smaller ones. This influence and the geographic concentration of their headquarters coupled with a lack of diversity in their management teams may create sub-optimal incentives for innovation. For example, they argued that VC investors are more likely to invest in start-ups that are geographically close to their headquarters, creating innovation incentives in areas and sectors far from those with the biggest economic needs. Third, the authors argued that the enormous amount of VC funding available in the 2010s may have resulted in a declining emphasis on governance. The increasing competition among VC funds seeking to invest in the most promising companies may have created room for more "founder friendly" VC deals that contribute less to raising the efficiency of innovative, early-stage start-ups.

2.2. Drivers of venture capital activity

Start-up activity is associated with considerable informational asymmetries and uncertainties. Venture capitalists seek to make informed investment decisions to maximize returns under these conditions. Investment decisions are related more to factors such as the time available to scrutinize firms and the expertise in a specific industry rather than the availability of venture funds (Gompers and Lerner, 2001; Sørensen, 2007). VC investment decisions take into consideration a series of micro aspects of targeted start-up firms, such as the quality of their management team, the industry in which they operate, the level of competition in that industry, the business model, and the product or technology offered.

Gompers et al. (2020) surveyed 885 institutional venture capitalists at 681 firms and concluded that the quality of the management team of the start-up is the most important attribute in VC investment decisions. To value the founders more than the business-related characteristics of start-ups is not a new development in venture investment. In the late 1990s, Feeney et al. (1999) interviewed approximately 150 venture capital investors to understand their investment decision-making processes. The authors found that venture capitalists value "owner" attributes, such as management track-record, integrity, and commitment, more than "business" prospects, such as risk-adjusted potential returns.

An additional, important aspect identified by both Feeney et al. (1999) and Gompers et al. (2020) is the availability of a feasible exit path for the venture investment, either via an IPO or through mergers and acquisitions. The most recent study explains that exit represents the main opportunity for VC investors to return capital to their investors and secure their profit share. A track-record of successful exits is also important for venture capitalists to establish a reputation and attract new investors (Gompers, 1996). Past and recent research suggests that geographic proximity also plays an important role in the investment decisions of VCs, because deals frequently involve post-entry, active monitoring, and board service (Lerner, 1995; Lerner and Nanda, 2020).

Additional aspects of the drivers of VC investment were discussed at an event organized by the U.S. Department of Justice (2020). At the event, Ram Shriram, an experienced VC investor and Google Board member, explained:

Fundamentally, the way I think about investing is in the person or the team first, then the technology and the defensibility, and then the market space. Because market spaces are fungible over time. It really comes down to how good the team is and whether they're able to pivot if they have to into a different space, morph the company, which all of which is possible early on in the life of a young company.

Other VC investors in the same workshop supported these views. However, some new criteria were added to the VC decision-making process. Kelland Reilly, another experienced VC investor, highlighted the fact that start-up investment decisions consider the scale and density of the data owned by the start-up and how the data are key for its business model. Start-ups that collect data and create feedback loops in which consumers provide data that improve the service and attract more consumers should attract more funding. In his view, this illustrates the current importance of data-driven business models to venture capitalists.

Other VC investors who participated in the event elaborated on investing in tech markets where platforms are omnipresent. Given this strong presence, start-ups often depend on services provided by the Big Techs, such as cloud services and map services. However, VC investors are wary about start-ups that rely heavily on platforms, because this dependence creates the risk of a single point of failure.

2.3. Big Tech start-up acquisitions, venture capital, and innovation

Acquisitions of start-ups by Google, Facebook, Amazon, Apple, and Microsoft can have several potential positive and negative effects on the likelihood of venture capitalists to invest in a start-up in the same industry segment. First, compared with venture capitalists, digital platforms have access to superior information about consumer markets. Therefore, they should be able to better assess the market potential of an early-stage start-up or an industry segment. In this case, a Big Tech start-up acquisition would be a positive sign that might attract venture capitalists to invest in start-ups of the same industry segment. Second, having a resourceful, large-scale, digital platform playing in an industry segment could encourage venture investment in start-ups focused on complementary innovations (Foerderer et al., 2018). Third, a Big Tech start-up acquisition might increase expectations that the Big Tech will acquire additional start-ups in the future. This would increase the likelihood that a venture investor will have a successful exit option by selling to the platform (U.S. Department of Justice, 2020).

On the other hand, the competition landscape after the entry of a Big Tech into a new industry segment through an acquisition might discourage venture investment in other start-ups in the same industry segment.[1] The risk of investing in a start-up might increase after a Big Tech acquisition in the same industry segment, because start-ups are dependent on a few Big Techs to host their technological solutions, distribute their apps to end users, and advertise their products to reach new customers. Moreover, an increased risk that start-ups in related activities might have their products copied by a competing Big Tech might also stifle venture investment. The overall, net effect of Big Tech acquisitions will depend on the relative strength of these ambiguous effects and needs to be established empirically.

Only a handful of studies have sought to unveil the effects of Big Tech start-up acquisitions on venture capital activity and on innovation. Kamepalli et al. (2020) argue that tech early adopters, anticipating the integration of an entrant's product by an incumbent platform, have fewer incentives to switch to the entrant's product. This effect reduces the revenue potential of entrants and their competitive positions. It creates “kill zones” for start-ups, who will face considerable struggles to obtain VC funding after a Big Tech acquisition in their industry segment. The study suggests that drops in the share of VC investment in the industry segments targeted by Facebook and Google major acquisitions, relative to total VC investment in the software industry, provide empirical support for this conceptual claim. The analysis is based on observations of nine selected, very large[2] start-up acquisitions by the Big Techs in the past twenty years.

Gautier and Lamesch (2021), analyzed data on 175 start-ups acquired by the five main, U.S., Big Techs between 2015 and 2017. The authors found that most of these start-ups were acquired in their early stage of development and had their product discontinued under its original name. The authors acknowledged that the data available for the study do not allow the exploration and confirmation of the reason behind each start-up acquisition. While fending off potential competition might be in play, other factors are compatible with the observations also. For example, many acquisitions are motivated by an interest in obtaining technological knowledge that can be integrated with other products and services. Thus, discontinuation of a product or brand name does not necessarily signal a negative effect on innovation.

Callander and Matouschek (2021) examined another aspect of the start-up innovation system by looking at the type of innovation. They concluded that start-up innovation driven by the prospect of an acquisition by a larger firm is less disruptive than activities by entrepreneurs and funders not motivated by it. In a scenario in which founders anticipate a sellout to a Big Tech, they seek to maximize profit pre-acquisition to achieve a higher start-up valuation. This is an interesting observation, but disruption is only one type of innovation and not necessarily the most transformative one. For example, a less disruptive innovation diffused widely by a Big Tech company may create larger benefits than a more disruptive innovation that is not widely adopted.

Our study complements these contributions with a detailed examination of the broader historical patterns. It analyzes the effects of 392 start-up acquisitions made since 2010 by Google, Facebook, Apple, Amazon, and Microsoft in 173 segments of the tech industry. Instead of measuring the variation in the share of VC investment driven to the industry segments that received those acquisitions, we focused on identifying changes in the total number of VC deals and the total amount of VC investment attributable to Big Tech start-up acquisitions. Furthermore, our empirical approach included as control variables the total number of M&As and IPOs per industry segment, because Big Tech companies are not necessarily unique or the biggest acquirers of start-ups.

3. Data

Our empirical analysis relies on data about venture capital deals, Big Tech start-up acquisitions, IPOs, and M&As of VC-backed firms that were consummated between January 1, 2010, and December 31, 2020. This information was retrieved from the database gathered by CB Insights.[3] This source classifies each start-up as belonging to twenty economic sectors and hundreds of industries and subindustries. The dataset contains information about a variety of features of each deal, such as the name of the start-up that received the VC funding, its location (continent, country, state, and city), the amount funded in the deal, and the investment round (Series A to E), day, month, and year when each deal was closed.[4] Because of use conditions imposed by CB Insights, the dataset to which we had access includes only information of the two main, tech-related economic sectors: Internet, and Mobile Telecommunications.

These two economic sectors alone comprise approximately 54% of the total 80,695 VC deals reported by CB Insights between 2010 and 2020. More important, they account for 404 or approximately 70% of the total 582 Big Tech, start-up acquisitions that occurred in the same period. The Big Tech start-up acquisitions were heavily concentrated in four of the industries that comprise these two economic sectors: Internet Software & Services, eCommerce, Mo-

[1] Although the line of business pursued by some start-ups may be folded after an acquisition, which would decrease competition in this market segment, there is no empirical evidence in the literature to suggest that this happens systematically in the tech industry. In an empirical study of the pharmaceutical industry, Cunningham et al. (2021) found that 5.3–7.4% of acquisitions in their sample led to a termination of the project.

[2] All acquisitions are valued above US$ 500 million, a scale that puts the acquired companies into a special class of start-ups.

[3] The data were retrieved from the CB Insights business intelligence platform, available at https://www.cbinsights.com/, under a license provided to Michigan State University for research purposes.

[4] Our dataset does not include information on angel and seed investment, which can be considered the very early stages of venture capital infusion.

Table 1
VC investment activity in tech-related industries (2010–2020).

Panel:	Worldwide			United States			Europe		
Ind. Segments: *Variables*	All	Trt	Untrt	All	Trt	Untrt	All	Trt	Untrt
VC deals	32367	23726	8641	17238	12662	4576	5342	3676	1666
VC funding	749.3	464.6	284.7	335.4	213.4	122.0	72.4	51.7	20.7
Avg. VC Fun.	23.2	19.6	32.9	19.5	16.9	26.7	13.6	14.1	12.4
Plat. Acqui.	392	392	0	292	292	0	66	66	0
IPOs	1447	1074	373	446	311	135	260	162	98
M&As	6149	4971	1178	3951	3161	790	1118	714	404

Trt columns report descriptive data of treated industry segments only, whereas Untrt reports untreated industry segments only.
Industry segments that received treatment are those that had at least one Big Tech acquisition between 2010 and 2020.
VC funding is reported in billions of U.S. dollars.
Avg. VC Fun. reports the average amount of funding per VC deal, in millions of U.S. dollars.
Worldwide deals include all VC deals included in the dataset, regardless of the base country of the company that received the VC investment. For information on the distribution of the variables throughout different regions included in the dataset, please refer to Table II.1 in the Appendix II.

bile Commerce, and Mobile Software & Services. In fact, 392 of the 404 Big Tech start-up acquisitions happened in only these four industries. In addition, 32,367 or approximately 40% of all VC deals in this period targeted start-ups of these four industries, representing an investment of more than $750 billion to support innovation by tech-related start-ups.

Because our aim was to identify the effects of Big Tech start-up acquisitions on VC investment provided to other similar start-ups, we narrowed the analysis and focused on identifying the effects on the subindustry level under these four industries. With this approach, we grouped the 32,367 VC deals and 392 Big Tech start-up acquisitions into 173 unique, sector-industry-subindustry triads (hereinafter referred to as “industry segments”). The data were analyzed for 44 quarters from 2010 to 2020, for a total of 7612 observations. Appendix I provides further details for each industry segment. From the CB Insights database, we also retrieved information about the number of IPOs and M&As of VC-backed companies for each industry segment. This allowed us to create fully balanced panel datasets of total VC-deals, VC-funding, Big Tech start-up acquisitions, IPOs, and M&As of VC-backed companies, per industry segment per quarter for different geographic settings. With the information of total VC deals and amount of VC funding, we could also calculate the average VC funding per deal, industry segment, and quarter. This resulted in an unbalanced panel dataset with observations for the industry segments and quarters with at least one VC deal.

Table 1 presents the geographic distributions of deals. We show data of all deals that happened worldwide between 2010 and 2020 as well as information on deals involving only U.S.-based start-ups and those involving only European-based start-ups. The table also provides a breakdown of the variables for industry segments that received no Big Tech start-up acquisition between 2010 and 2020 (columns labeled as “Untrt”), and those that were affected by at least one acquisition (columns labeled as “Trt”). The table illustrates that VC deals and funding, IPO, and M&A activity are much more intense in treated industry segments of all geographic breakdowns.

Table 2 provides descriptive statistics per quarter of all variables for each of the three geographic breakdowns, as well as for all treated and untreated industry segments. It is important to note that the mean number of VC deals and funding per quarter for deals that happened worldwide is greater than the simple sum of the means found for U.S.-only and European-only deals, because the panel dataset containing worldwide deals includes information about many other countries. Table II.1 of Appendix II shows a summary of the distribution of the variables per region. The quarterly development of these variables from 2010 to 2020 across all industry segments is presented in Appendix II (Figs. II.1, II.2, and II.3) for each of the three geographic breakdowns.

A quick analysis of Table 2 reveals that the average number of VC deals, IPOs, M&As and the amount of VC funding per quarter and industry segment is greater for those industry segments that receive a Big Tech start-up acquisition at least once. This may suggest the existence of some association between these acquisitions and the VC activity. For example, according to the literature reviewed in Section 2, Big Techs and venture capitalists may have similar preferences about the industry segments in which they wish to invest. Also, VC investors may be compelled to invest in start-ups of industry segments previously chosen by a Big Tech for an acquisition.

On the other hand, we can also note that the average VC funding per deal is higher in untreated industry segments. There are several explanations for this observation. It could imply that start-ups from around the world are less funded in treated industry segments. Alternatively, it could imply that because treated industry segments have a bigger start-up ecosystem, they allow VC investors to further diversify their portfolios instead of concentrating big amounts of investment in a few start-ups. In the next sections we examine in detail such potential associations and effects.

Worldwide deals include all VC deals included in the dataset, regardless of the base country of the company that received the VC investment. For information on the distribution of the variables throughout different regions included in the dataset, please refer to Table II.1 in the Appendix II.

Fig. 1 shows the distribution of treated industry segments and quarters (i.e., those that have received at least one Big Tech start-up acquisition) among all industry segments and quarters included in the dataset. It provides evidence that a given industry segment may have received Big Tech start-up acquisitions in several quarters during the 2010–2020 period. Big Tech start-up acquisitions in the United States and Europe follow a similar pattern. The implications of this characteristic of our data on the estimation procedures are discussed in detail in the next sections.

4. Empirical strategy

In the following subsections we specify the two empirical approaches used to identify the effects of Big Tech start-up acquisitions on venture capital activity. Section 4.1 details a strategy to investigate a potential association between the level (number) of

Table 2
Descriptive statistics.

Panel:	Worldwide				United States				Europe			
Variable	Obs	Mean	Min	Max	Obs	Mean	Min	Max	Obs	Mean	Min	Max
VC deals	7612	4.25	0	68	7612	2.26	0	44	7612	0.70	0	21
		(7.82)				(4.47)				(1.67)		
VC funding	7612	98.44	0	14386.99	7612	44.06	0	4100	7612	9.52	0	616.72
		(336.07)				(130.69)				(36.42)		
Avg VC fund.	4647	22.84	0.07	2000	3840	20.62	0.02	1366.67	2282	12.32	0.02	360
		(68.91)				(49.37)				(21.89)		
Platform acq.	7612	0.05	0	5	7612	0.04	0	4	7612	0.01	0	1
		(0.25)				(0.21)				(0.01)		
IPOs	7612	0.19	0	7	7612	0.06	0	4	7612	0.03	0	5
		(0.60)				(0.28)				(0.20)		
M&As	7612	0.81	0	19	7612	0.52	0	13	7612	0.15	0	9
		(1.72)				(1.23)				(0.48)		
Treated industry segments												
VC deals	3608	6.58	0	68	3300	3.84	0	44	1760	0.95	0	17
		(9.36)				(5.80)				(1.66)		
VC funding	3608	128.78	0	14386.99	3300	64.66	0	1591.22	1760	11.76	0	555.50
		(363.33)				(133.75)				(36.17)		
Avg VC fund.	2993	18.18	0.1	1010.42	2372	17.09	0.02	644.18	775	11.83	0.02	360
		(38.69)				(29.87)				(24.75)		
Platform acq.	3608	0.11	0	5	3300	0.09	0	4	1760	0.04	0	1
		(0.35)				(0.32)				(0.19)		
IPOs	3608	0.30	0	7	3300	0.09	0	4	1760	0.06	0	3
		(0.73)				(0.35)				(0.26)		
M&As	3608	1.38	0	19	3300	0.96	0	13	1760	0.23	0	4
		(2.19)				(1.65)	0			(0.54)		
Untreated industry segments												
VC deals	4004	2.16	0	68	4312	1.06	0	34	5852	0.628	0	21
		(5.31)				(2.48)				(1.671)		
VC funding	4004	71.10	0	7373.39	4312	28.29	0	4100	5852	8.843	0	616.72
		(306.95)				(126.06)				(36.472)		
Avg VC fund.	1654	31.28	0.07	2000	1468	26.33	0.07	1366.67	1507	12.57	0.05	291.5
		(102.62)				(69.89)				(20.27)		
Platform acq.	4004	0	0	0	4312	0	0	0	5852	0	0	0
		(0)				(0)				(0)		
IPOs	4004	0.09	0	7	4312	0.031	0	4	5852	0.028	0	5
		(0.42)				(0.20)				(0.186)		
M&As	4004	0.29	0	11	4312	0.18	0	7	5852	0.122	0	9
		(0.85)				(0.57)				(0.456)		

Descriptive statistics calculated per quarter over the 2010-2020 period.
VC funding is reported in millions of U.S. dollars.
Avg VC fund. reports the average amount of funding per VC deal per industry segment per quarter, in millions of U.S. dollars, only considering industry segments and quarters that received at least one VC deal.
Worldwide deals include all VC deals included in the dataset, regardless of the base country of the company that received the VC investment. For information on the distribution of variables throughout different regions included in the dataset, please refer to Table II.1 in the Appendix II.
Treated industry segments are those that had at least one Big Tech acquisition between 2010 and 2020.

Big Tech start-up acquisitions in a given industry segment and the level of its VC activity. In addition, Section 4.2 presents a strategy to compare VC activity in industry segments that received at least one Big Tech start-up acquisition (treatment) between 2010 and the end of 2020 with those that did not receive any, to identify the average effect of these acquisitions on VC activity.

4.1. Response of VC activity to Big Tech start-up acquisitions

Let us consider that an industry segment $i \in I$ receives in each time period $t \in T$ a total amount of venture-capital funding ($vcfund_{i,t}$), through several venture-capital deals ($vcdeals_{i,t}$), to support the creation and delivery of innovative products and services. The average VC funding per deal in a given industry segment i and quarter t ($avg\_vcfund_{i,t}$) is calculated as the ratio between $vcfund_{i,t}$ and $vcdeals_{i,t}$. The venture capital investment to support innovation may be affected by present or past Big Tech start-up acquisitions in each industry segment. For modeling purposes, consider $plat_{i,t}$ as the total number of Big Tech start-up acquisitions that happened in a given industry segment i in period t. As detailed in Section 30, the Big Techs have acquired more than 500 start-ups in the last decade.

As suggested by the literature reviewed in the previous section and considering data availability at the industry-segment level, we control the effect of Big Tech start-up acquisitions on venture capital activity by other exit events that may have an effect on venture investment, namely the total number of IPOs ($ipo_{i,t}$) and M&As of VC-backed start-ups ($ma_{i,t}$). To differentiate the effect of Big Tech start-up acquisitions from general exit events, it is important to control for other exit events that may affect venture capital activity. This is because the interest of a digital platform in an industry segment may have a special impact on the risk assessment performed by a venture capitalist before investing in a start-up, as discussed in Section 2. In addition, controlling for the number of IPOs per industry segment rules out the effect of time-evolving market scalability of each industry segment on the attractiveness of its start-ups to receive venture investment.[5]

[5] More IPOs may suggest that the addressable market of start-ups of a given industry segment is big enough to support companies valued at the billion dollar-level, which may attract more VC investment. Gompers et al. (2020) found that

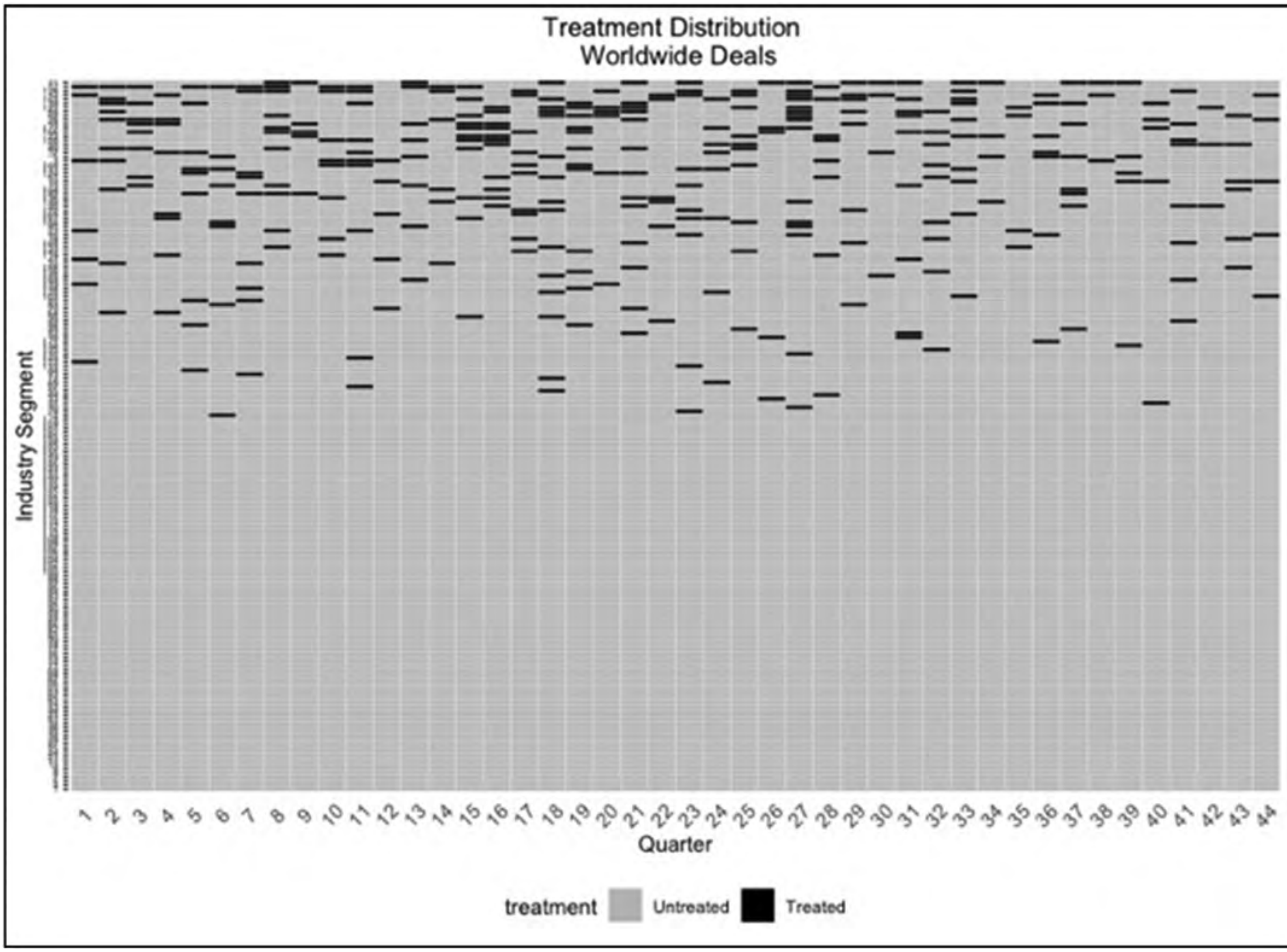

Fig. 1. Distribution of treatment through industry segments and quarters worldwide.

We also control for unobserved industry (c_i) and time-fixed effects (λ_t). c_i accounts for time-invariant characteristics of each industry segment. These include the presence of low sunk costs and high economies of scope and scale that may raise expected payoffs in certain technology-intensive industry segments and thus attract more venture investment. λ_t allows us to rule out the effects of economic cycles and other time-specific, exogenous, economic shocks that may influence venture capital activity, e.g., the COVID-19 pandemic. Based on data availability (as detailed Section 3), our choice for performing the analysis at the industry level does not allow us to control for time-varying, start-up-specific characteristics, such as the experience of its leadership team. The implications of this constraint on our empirical approach to the interpretation of the estimation results are discussed later in Section 5.

Finally, it is important to notice that we foresee a very dynamic relationship between the Big Tech start-up acquisitions and venture capital activity. Because venture capitalists internalize the new market conditions of the industry segment, the impact of an increased level of acquisitions made by Big Techs in a certain industry segment may not be visible in the same month or quarter, but only in the near future. To capture these short-run effects, we include in the model three lagged terms of the explanatory variables.[6] Eq. (1) presents the dynamic equation that we are interested in estimating. The exponential functional form was chosen because both $vcdeals_{i,t}$, $vcfund_{i,t}$, and the average VC funding per deal in a given industry segment i and quarter t ($avg\_vcfund_{i,t}$) receive only zero or strictly positive values. This choice is further discussed in Section 0, after we detail the dataset used in the econometric estimation.

$$Y^{\nu}_{i,t} = c_i \varepsilon_{i,t} \exp(\alpha^{\nu} + \beta^{\nu}_0 plat_{i,t} + \beta^{\nu}_1 plat_{i,t-1} + \beta^{\nu}_2 plat_{i,t-2} + \beta^{\nu}_3 plat_{i,t-3} + X_{i,t}\gamma^{\nu}_0 + X_{i,t-1}\gamma^{\nu}_1 + X_{i,t-2}\gamma^{\nu}_2 + X_{i,t-3}\gamma^{\nu}_3 + \lambda_t) \tag{1}$$

In Eq. (1), the dependent variable $Y^{\nu}_{i,t}$ may be either $vcdeals_{i,t}$, $vcfund_{i,t}$, or $avg\_vcfund_{i,t}$, as indicated by the respective superscript $\nu = \{vcd, vcf, vcaf\}$. The constant α is a cross-sectional and time-invariant mean of the dependent variable, whereas $\varepsilon_{i,t}$ is a specification error term. Furthermore, $X_{i,t-k}\gamma^{\nu}_k = \gamma^{\nu}_{1,k} ipo_{i,t-k} + \gamma^{\nu}_{2,k} ma_{i,t-k}$, for any $k = \{0, 1, 2, 3\}$. The coefficients of interest are β^{ν}_0, β^{ν}_1, β^{ν}_2, and β^{ν}_3, the semi-elasticities of $Y^{\nu}_{i,t}$ with respect to $plat_{i,t-k}$. In other words, they measure the average marginal effect on the venture capital activity in the current and future time periods associated with a Big Tech start-up acquisition that happened in an industry segment i in the current period.

past IPOs are an important sign for VC investors, who regard the feasibility of an exit path through an IPO for their investment in a start-up.

[6] Although more lagged terms could be included, we opted to limit the empirical investigation to one year (the quarter of the acquisition and three quarters after), because our focus is to identify the short-term effects of big tech start-up acquisitions on VC activity.

4.2. Investigation of causal effects of big-tech start-up acquisitions on venture capital activity

To investigate whether big-tech start-up acquisitions have a causal effect on $vcdeals_{i,t}$, $vcfund_{i,t}$, and $avg\_vcfund_{i,t}$, we used a dynamic differences-in-differences (DiD) setup with heterogenous treatment effects over time. However, it is important to consider that our treatment (a Big Tech start-up acquisition in a given industry segment) may happen multiple times over the course of years in the same industry segment (as detailed in Section 6 below), and will have short-term effects (e.g., lasting a few quarters), as the reviewed literature suggests. In other words, our units of analysis (industry segments) may switch from untreated to treated to untreated status multiple times over the course of the observation period.

Because of this switching characteristic of our treatment, well-known dynamic DiD empirical strategies (e.g., Goodman-Bacon, 2018; Athey and Imbens, 2021) cannot correctly identify the average treatment effects of Big Tech start-up acquisitions on venture capital activity. One alternative would be to investigate only the effects on industry segments that received treatment only once. This would substantively affect the efficiency of our estimation and the robustness of our results, because most of the Big Tech start-up acquisitions happen in industry segments that have already received treatment in the past. Therefore, to identify the average effects of a Big Tech start-up acquisition (the treatment) on $vcdeals_{i,t}$, $vcfund_{i,t}$, and $avg\_vcfund_{i,t}$, we utilize the empirical strategy proposed by Imai et al. (2021). This strategy uses matching methods to identify causal inference in panel datasets with switching treatment status. We provide further details of the estimation methods in Section 6.

For now, assume $treat_{i,t}$ is a binomial variable that indicates whether the industry segment i received treatment in time t. Thus, $treat_{i,t}$ equals 1 when $plat_{i,t}$ is greater than zero and equals 0 otherwise. Let L be the number of time periods before the treatment during which we want to assure that treated and untreated industry segments have the same history of treatment ($\{treat_{i,t-l}\}_{l=2}^{L}$). For example, if the treatment happened in time $t = 5$, and $L = 3$, we would want to compare industry segments treated in $t = 5$ with industry segments untreated in period $t = 5$ but with the same history of treatment in periods $t = \{2,3,4\}$. Furthermore, consider F the number of time periods after the treatment during which one wants to investigate the average treatment effects on the treated units (ATTs). For example, if treatment happened in period t and $F = 3$, one is interested in investigating the ATTs in periods t, $t+1$, $t+2$, and $t+3$. Once defined, these two parameters, L and F, the dynamic effects that we want to identify can be defined by Eq. (2).[7]

$$\delta^{v}(F,L) = \mathbb{E}\{Y^{v}_{i,t+F}\left(treat_{i,t}=1, treat_{i,t-1}=0, \{treat_{i,t-l}\}_{l=2}^{L}\right) - Y^{v}_{i,t+F}\left(treat_{i,t}=0, treat_{i,t-1}=0, \{treat_{i,t-l}\}_{l=2}^{L}\right) | treat_{i,t} = 1, treat_{i,t-1}=0\} \qquad (2)$$

For example, $\delta^{vcd}(2,\ 4)$ represents the average difference of the total number of VC deals between a treated industry segment and an untreated industry segment, assessed up to two quarters after the treatment among matched treated and untreated industry segments with the same history of treatment in in the second, third, and fourth periods before the treatment.

This empirical approach has an intrinsic limitation to identify truly causal effects of Big Tech start-up acquisitions on VC activity. This is because our data do not allow us to control for all, time-varying factors that may have an effect on VC investment decisions. Our specification assumes that the level of IPO and M&A activity controls the level of attractiveness of each industry segment over time. However, factors, such as the level of expertise of VC investors in a given industry segment or the average quality of the start-up's management team of each industry segment may also vary over the time but cannot be controlled with the available data. The implications of such limitations on our empirical approach to the interpretation of the estimation results are discussed in Section 6.

5. Response of VC activity to Big Tech start-up acquisitions

Table 3 shows results of the two-way fixed effects estimation of the dynamic model specified by Eq. (1), using the entire sample of VC capital deals worldwide between 2010 and 2020. Columns 1, 2, and 3 present estimates for the impact of platform acquisitions on the total number for VC deals per industry segment per quarter. Columns 4, 5, and 6 report estimates for the impact on total VC funding per industry segment per quarter. For brevity, the estimates for the impact of Big Tech start-up acquisitions on average VC funding per deal and quarter are not reported in Table 3. None of them were found to be statistically significant, but they can be reviewed in detail in Table II.2 of Appendix II. Standard errors of the estimates reported in Table 3 were clustered at the industry segment level and are robust to heteroskedasticity. Columns 1 and 4 report estimates of the dynamic model of Eq. (1) but without including the controlling variables $ipo_{i,t-k}$ and $ma_{i,t-k}$, for $k = \{0, 1, 2, 3\}$; columns 2 and 5 present estimates with the inclusion of such controlling variables.

Because the dependent variables are non-negative, and hence an exponential estimation model is specified by Eq. (1), we made use of a fixed effects Poisson estimator. One advantage of using a Poisson estimator instead of a linear model is that it allows always to have positive, predicted results. In addition, we do not have to deal with log transformations such as *log(1+y)*, typically implemented to estimate semi-elasticities through linear models when the dependent variable y equals zero for some observations (Wooldridge, 2010, p. 723). The results suggest a positive, statistically significant association between platform acquisitions and venture capital activity in the near future (two to three quarters ahead), after controlling for other exit events as well as time- and industry-segment-specific heterogeneity.

Two attractive features of the Poisson estimator are that it allows the assumed Poisson distribution of the dependent variable to be arbitrarily mis-specified, and it permits the presence of any serial correlation (Wooldridge, 2010). However, because the panel dataset includes information from 44 time periods (quarters) and 173 industry segments,[8] columns 3 and 6 present estimates obtained after addressing serial correlation by including multiple lags of the dependent variables among the regressors.[9] Furthermore, as an additional robustness check, we added to the estimation models of columns 3 and 6 forward regressors $plat_{i,t+1}$, $ipo_{i,t+1}$, and $ma_{i,t+1}$. This procedure allowed us to test the strict exogeneity assumption of the independent variables of our estimation models (Wooldridge, 2010, p. 764). The results, reported in columns (3.F) and (6.F) of Table II.2 of Appendix II, showed no statistically significant effects of current shocks in the level of VC deals and funding

[7] Details on the selection of L and F are provided in Section 6.

[8] The modern, econometric literature does not consider serial correlation a big issue in a scenario of small T and large N. Because T in our dataset is relatively large (44 quarters), we opted to deal with serial correlation explicitly in the model specification. However, results shown in columns 3 and 6 are not significantly different from those in columns 2 and 5, because the Poisson regressor is robust under serial correlation.

[9] Four lagged dependent variables were included in the model of column 3, whereas only one was in the model of column 6, because any additional lagged terms of the dependent variables were found to be non-statistically significant.

Table 3
Results of the two-way fixed effects Poisson estimation - worldwide VC activity.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	VC Deals	VC Deals	VC Deals	VC Funding	VC Funding	VC Funding
Independent variables						
plat	0.0298	0.0183	0.0229	0.0279	0.0187	0.0197
	(0.0317)	(0.0318)	(0.0279)	(0.0762)	(0.0759)	(0.0751)
plat (1 lag)	0.0627	0.0509	0.0474*	0.0734	0.0698	0.0712
	(0.0411)	(0.0397)	(0.0259)	(0.0725)	(0.0792)	(0.0781)
plat (2 lags)	0.0812**	0.0711**	0.0704***	0.195*	0.198*	0.198*
	(0.0346)	(0.0338)	(0.0197)	(0.113)	(0.110)	(0.110)
plat (3 lags)	0.0668**	0.0616*	0.0610***	0.148*	0.119	0.117
	(0.0309)	(0.0323)	(0.0207)	(0.0844)	(0.0839)	(0.0829)
Combined effects						
plat	0.2405*	0.2019*	0.2017***	0.4444	0.4049	0.4057
	(0.1255)	(0.1217)	(0.006)	(0.2729)	(0.2638)	(0.2604)
Observations	7093	7093	6920	7093	7093	7093

Estimation models reported in columns (2), (3), (5) and (6) include current and t-1 to t-3 lagged controlling variables. Estimation model reported in column (3) also include t-1 to t-4 lagged dependent variables for correcting for serial correlation, whereas the estimation model reported in column (6) also include a t-1 lagged dependent variable. Additional lags were not found statistically significant.
Standard errors in parentheses were clustered at the industry segment level and are robust to heteroskedasticity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

on future levels of platform acquisitions per industry segment per quarter.

As the results reported in columns 3 and 6 of Table 3 suggest, the semi-elasticities of exit events with respect to the total number of VC deals per industry segment per quarter in the near future are highly statistically significant. But the effects on the total VC funding, although positive on average, are not statistically different from zero at the 5% level in any case. They suggest an increase of 4.74%, 7.04%, and 6.10%, respectively, in the number of VC deals in a given industry segment in the three quarters that follow a quarter in which a Big Tech start-up acquisition happened in that industry segment. Parameter estimates for the control variables were also statistically significant and can be reviewed in detail in Table II.2 in of Appendix II.

Furthermore, we found a positive combined effect of 20.17% of the platform acquisition on the total number of VC deals from the quarter of the acquisition until the third quarter after an acquisition, with a 95% confidence interval of [5.93%, 34.41%].[10] These results support the claim made in Section 2.3 that a Big Tech start-up acquisition in a given industry segment produces a positive sign to venture capitalists that increases their interest in investing in start-ups of that industry segment.[11] On the other hand, we found that the combined effect of acquisitions of start-ups by the Big Techs on the total amount of VC funding in the industry segment that received the shock is not statistically different from zero.

Tables 4 and 5 show results of similar, two-way, fixed effects Poisson estimation, but using only U.S.-based or European-based VC deals, platform acquisitions, IPOs, and M&As of VC-backed start-ups, respectively. Estimates for the impact on the average VC funding per deal and quarter were omitted for brevity, because they were statistically not significant for either U.S.-based or European-based VC deals, but they are reported in detail in Tables II.3 and II.4 of Appendix II.[12] Standard errors of the estimates reported were also clustered on the industry-segment level and are robust to heteroskedasticity. Furthermore, similar additional robustness checks were performed and suggested that the assumption of strict exogeneity of the regressors strongly holds for the estimation models reported in columns 3 and 6 of both tables. Detailed results of this test and complete results with estimates of all control variables are reported in Tables II.3 and II.4 of Appendix II.

The results regarding the effects of Big Tech acquisitions of U.S.-based start-ups, (found through the most robust estimation models, reported in columns 3 and 6 of Table 4) suggest a highly statistically significant, positive impact on both the total number of VC deals and total amount of VC funding per industry segment per quarter in the two quarters that follow an acquisition. The results reveal an average increase of 7.86%, and 8.47% respectively, in the total number of VC deals in a given industry segment in the two quarters that follow a quarter in which a Big Tech start-up acquisition occurred in a given industry segment. Furthermore, increases of 11.00 and 14.70% in the total amount of VC funding were found in the same period.

The results suggest positive increases of 21.05% and 30.71% in the total number of VC deals and in the total amount of VC funding, respectively, from the quarter of the acquisition until the third quarter after the acquisition, with a 95% confidence interval of [7.31%, 34.79%] and [2.58%, 58.84%], respectively. Although these confidence intervals are wide, they provide empirical ground for the claim that acquisitions of U.S.-based start-ups by the Big Techs produce positive incentives for innovation in the industry segments of the U.S. tech ecosystem, which receive such acquisitions. Because the Big Tech start-up acquisitions attract more venture capital to fund other start-ups of that same industry segments, an increased innovation outcome is expected. A vast empirical literature has established a strong, positive, causal relationship between venture capital investment and innovation.

The results presented in Table 5 reveal that this positive effect is even stronger in Europe. The findings challenge claims that associate Big Tech acquisitions with discouragement for VC investment in other European start-ups playing in the same industry segment. Increases of 11 and 31% in the total number of VC deals were also

[10] The combined estimate is calculated through the linear combination of the four estimates found for the variables $plat_{i,t-k}$, for $k = \{0, 1, 2, 3\}$.

[11] Section 2.3 suggests three main reasons for an increase in VC activity in response to big tech start-up acquisitions: (i) a positive signal of market potential, (ii) an increased incentive to VC investment in complementary innovation, and (iii) an increased prospect that the big tech will acquire additional start-ups of the same industry segment in the future. However, our dataset and empirical approach do not allow us to make conclusions on which of three factors or which combination of them influence the positive effects found.

[12] In the estimation models with no control variables and with control variables, a 47% increase was found on the average VC funding per deal in European-based deals, statistically significant at 10%. However, when we include lagged terms of the dependent variable in the estimation to make it robust to serial correlation, no statistically significant estimates were found.

Table 4
Results of the two-way fixed effects Poisson estimation - United States.

Model **Dependent variable**	(1) VC Deals	(2) VC Deals	(3) VC Deals	(4) VC Funding	(5) VC Funding	(6) VC Funding
Independent variables						
plat	0.0205	0.00550	0.0161	0.0823	0.0492	0.0317
	(0.0340)	(0.0325)	(0.0263)	(0.0677)	(0.0634)	(0.0604)
plat (1 lag)	0.0971**	0.0789**	0.0786***	0.0999***	0.0782**	0.110**
	(0.0398)	(0.0360)	(0.0245)	(0.0346)	(0.0347)	(0.0474)
plat (2 lags)	0.125***	0.104***	0.0847***	0.306***	0.283***	0.147**
	(0.0351)	(0.0345)	(0.0262)	(0.111)	(0.106)	(0.0608)
plat (3 lags)	0.0606	0.0506	0.0310	0.195*	0.160	0.0179
	(0.0410)	(0.0398)	(0.0307)	(0.102)	(0.0984)	(0.0564)
Combined effects						
plat	0.3031**	0.2385**	0.2105***	0.6835**	0.5701**	0.3071**
	(0.1314)	(0.1205)	(0.0701)	(0.2660)	(0.2339)	(0.1435)
Observations	6519	6519	6201	6519	6519	6201

Estimation models reported in columns (2), (3), (5) and (6) include current and t-1 to t-3 lagged controlling variables. Estimation models reported in columns (3) and (6) also include t-1 to t-5 lagged dependent variables for correcting for serial correlation. Additional lags were not found statistically significant.
Standard errors in parentheses were clustered at the industry segment level and are robust to heteroskedasticity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5
Results of the two-way fixed effects Poisson estimation - Europe.

Model **Dependent variable**	(1) VC Deals	(2) VC Deals	(3) VC Deals	(4) VC Funding	(5) VC Funding	(6) VC Funding
Independent variables						
plat	-0.0951	-0.0986	-0.0993	-0.225	-0.264	-0.259
	(0.120)	(0.120)	(0.123)	(0.168)	(0.169)	(0.167)
plat (1 lag)	0.0646	0.0665	0.110	0.680*	0.659*	0.667*
	(0.119)	(0.119)	(0.110)	(0.359)	(0.374)	(0.370)
plat (2 lags)	0.236*	0.248*	0.310**	0.651**	0.666**	0.657**
	(0.143)	(0.149)	(0.153)	(0.302)	(0.312)	(0.316)
plat (3 lags)	-0.104	-0.0964	-0.0720	0.221	0.248	0.241
	(0.140)	(0.147)	(0.143)	(0.377)	(0.382)	(0.382)
Combined effects						
plat	0.1012	0.1193	0.2490	1.3268**	1.3092**	1.3062**
	(0.3449)	(0.3548)	(0.3465)	(0.6258)	(0.6556)	(0.6458)
Observations	5494	5494	5494	5494	5494	5494

Estimation models reported in columns (2), (3), (5) and (6) include current and t-1 to t-3 lagged acquisition variables. Estimation models reported in columns (3) and (6) also include t-1 to t-3 lagged dependent variables to correct for serial correlation. Additional lags were not found statistically significant.
Standard errors in parentheses were clustered at the industry segment level and are robust to heteroskedasticity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

found in the first and second quarter following the quarter of the acquisition, as reported in column 3 of Table 5, although only the impact found in the second quarter is statistically different than zero. On the other hand, the results reported in column 6 reveal strong, positive, statistically significant average increases of 65.90%, and 66.60%, respectively, on the total amount of VC funding in a given industry segment in the two quarters that follow a quarter in which a Big Tech start-up acquisition happened in a given industry segment. These results suggest a strong positive combined effect of 130.62% on the total amount of VC funding from the quarter of the acquisition until the third quarter after the acquisition, although with a very wide 95% confidence interval of [4.03%, 257.20%].

One explanation for a stronger effect of Big Tech start-up acquisitions in Europe compared to the United States may be the highly dynamic venture capital activity in the latter. VC investors in the United States may have more information about promising industries and start-ups and more options to decide about the allocation of venture funding without using Big Tech start-up acquisitions as a bellwether.

Finally, our results do not support a clear association between an increase in the number of Big Tech start-up acquisitions and changes on the average amount of VC funding per deal per quarter in any of the three geographical breakdowns. Thus, although industry segments that have received at least one Big Tech start-up acquisition between 2010 and 2020 have a lower average VC funding per deal per quarter (as reported in Table 2 of Section 3) when compared to untreated industry segments, our findings suggest that this might not happen as a response to an increase in the number of start-up acquisitions performed by the Big Techs. The lower average funding per deal per quarter in treated industry segments might result from a more diversified start-up ecosystem, as already discussed in Section 3, although further research should be done to confirm such a claim.

6. Average effects of Big Tech start-up acquisitions on VC activity

For estimating the average treatment effects of Big Tech start-up acquisitions on venture capital activity, $\delta^{v}(F, L)$, specified in Eq. (2) of Section 4, we relied on the estimation procedure proposed by Imai et al. (2021). In summary, for each treated observation, we found a set of control observations with the same treatment history, up to a certain number (L) of time periods before the treatment. After finding a matched set for each treated observation, we used a propensity score weighting (PSW) procedure to estimate a counterfactual outcome for each treated observation, based on the weighted average of the outcomes of the units included in each matched set. Then, we applied the differences-in-differences estimator, using only the outcomes of treated observations and their respective counterfactual outcome.

6.1. Identification assumptions

This estimation approach makes three main assumptions for identifying the ATTs of staggered treatment with switching treatment status. The first assumption is that there are no spillover effects of the treatment. For our study, this requires the assumption to hold that a Big Tech start-up acquisition in an industry segment does not affect VC activity in other industry segments. Considering that VC funding has been massively available, and that our reviewed literature suggests that VC investors are more constrained by the time to scrutinize different investment opportunities than by the availability of capital, we believe it is reasonable to maintain this assumption for the purposes of this paper, with the goal to conduct additional analyses in the future. However, if this plausible assumption does not hold, the treatment effects identified with this approach may be biased upwards.

The second identification assumption is that the treatment effects on the outcome variable are limited in time (up to L time periods). This assumption is consistent with our empirical data and is supported by the reviewed research literature (see Section 0), which suggests a short-term effect of Big Tech start-up acquisitions on VC activity.

The third assumption is that, after conditioning on the treatment, covariates, and outcome variable histories (up to L time periods), parallel trends exist between treated and hypothesized counterfactual untreated observations that were very likely to be treated. To maintain this assumption, these counterfactual observations were calculated by adopting a matching procedure with weighting proposed by Imai et al. (2021), as detailed in the next subsections. Eq. (3) formalizes such a parallel trends assumption.

$$\begin{aligned}&\mathrm{E}\left[Y^{v}_{i,t+F}\left(treat_{i,t}=0, treat_{i,t-1}=0, \{treat_{i,t-l}\}_{l=2}^{L}\right) - Y^{v}_{i,t-1}\middle| treat_{i,t}=1, treat_{i,t-1}=0,\ \left\{treat_{i,t-l}, Y^{v}_{i,t-l}\right\}_{l=2}^{L}, \{ipo_{i,t-l}\}_{l=0}^{L}, \{ma_{i,t-l}\}_{l=0}^{L}\right]\\ &= \mathbb{E}\left[\left(treat_{i,t}=0, treat_{i,t-1}=0, \{treat_{i,t-l}\}_{l=2}^{L}\right) - Y^{v}_{i,t-1}\middle| treat_{i,t}=0, treat_{i,t-1}=0,\ \left\{treat_{i,t-l}, Y^{v}_{i,t-l}\right\}_{l=2}^{L}, \{ipo_{i,t-l}\}_{l=0}^{L}, \{ma_{i,t-l}\}_{l=0}^{L}\right]\end{aligned} \tag{3}$$

6.2. Matching procedure

The first step of the matching procedure was to select the number of time periods L before the treatment during which we want to assure that treated and untreated industry segments have the same history of treatment. By choosing L, we assume a limited carryover effect of past treatment on the outcome variables (up to L time periods). Although a large L makes this assumption less restrictive, it may reduce the chance of finding in the matching procedure controlling industry segments with the same history of treatment as the treated industry segments and potentially yielding less precise estimates. We chose $L = 3$ for coherence with the results of the two-way fixed effects estimation, presented in Section 5, that show a positive, statistically significant, marginal effect of platform acquisitions on VC activity in the first three quarters following an acquisition.

Once L had been defined, we matched treated observations with untreated observations of the same time that had the same treatment history in t-1, t-2, and t-3. This allowed us to build a matched set of control observations for each treated observation. Fig. 2 illustrates the matching procedure.

Time

Units	t=1	t=2	t=3	t=4	t=5	t=6
i=1	0	0	0	0	0	0
i=2	0	0	1	0	1	0
i=3	0	0	0	0	0	0
i=4	0	0	0	0	0	0
i=5	0	0	0	0	0	0
i=6	0	0	0	1	0	0
i=7	0	0	0	0	0	0
i=8	0	0	0	0	0	0
i=9	0	0	0	0	0	0
i=10	0	1	0	0	0	0
i=11	0	0	0	0	0	0
i=12	0	0	0	0	0	0
i=13	0	0	0	0	0	1

Fig. 2. Illustration of the matching procedure for $L = 3$
Note: Each treatment observation, marked as 1, has a set of same time control matched observations, marked as 0 and colored with the same color as the treated observation, that have the same treatment history in the previous two time periods. Note that, in this example, no control units were assigned for the treatment of observation (i=2,$t = 5$), because none of the control observations of the same time period $t = 5$ have the same treatment history in $t = 2$, $t = 3$, and $t = 4$.

6.3. Weighting of matched control observations

As proposed by Imai et al. (2021), once the matched sets for each treatment observation had been found, we estimated the ATT of Big Tech start-up acquisitions on the total number of VC deals per industry segment per quarter, $\widehat{\delta^{vcd}(F, L)}$, on the total amount of VC funding per industry segment per quarter, $\widehat{\delta^{vcf}(F, L)}$ and on the average amount of VC funding per deal per industry segment per quarter, $\widehat{\delta^{vcaf}(F, L)}$. For each treated observation of industry segment i and quarter t, we estimated the counterfactual outcome $\widehat{Y^{v}_{i,t+F}}(treat_{i,t} = 0, treat_{i,t-1} = 0, \{treat_{i,t-l}\}_{l=2}^{L})$ by calculating the weighted average outcome of the control observations in each matched set.

We used the well-known, inverse propensity score weighting method (PSW) as proposed by Hirano et al. (2003). Essentially, based on its propensity score, we calculated a weight for each control observation included in a matched data set. A greater weight was assigned to control observations with a more similar history of covariates ($\{ipo_{i,t-l}\}_{l=0}^{L}, \{ma_{i,t-l}\}_{l=0}^{L}$) and outcome values ($\{Y^{v}_{i,t-l}\}_{l=2}^{L}$), compared to the treated observation. In other words, control observations with a propensity score closer to the propensity score of the treatment observation received greater weighting. This weighting procedure was important to provide support for the pre-treatment parallel trends assumption previously discussed. Other weighting methods, such as the propensity score matching (PSM) procedure, were also tested. They yielded similar results, but with more restrictive assumptions than the PSW method reported, thus supporting our choice of the PSW method.

The propensity score of each matched control observation was calculated as the conditional probability of treatment assignment given pre-treatment values of their covariates and outcome variables, as proposed by Rosenbaum and Rubin (1983).

Table 6
Results of DiD inference.

Panel	(1) Worldwide	(2) U.S.	(3) Europe	(4) Worldwide	(5) U.S.	(6) Europe	(7) Worldwide	(8) U.S.	(9) Europe
Dependent variable	VC Deals	VC Deals	VC Deals	VC Fund	VC Fund	VC Fund	Avg VC Fund	Avg VC Fund	Avg VC Fund
All treatment									
ATT	0.0637**	-0.0078	-0.0016	0.1892**	-0.0058	-0.0038	0.1332**	0.0365	0.0116
	(0.0295)	(0.0298)	(0.0532)	(0.0712)	(0.0758)	(0.1197)	(0.0621)	(0.063)	(0.1083)
ATT 1 quarter post	0.0309	0.0057	0.0944*	0.1422	-0.066	0.3397**	0.1526*	-0.0879	0.2882**
	(0.0338)	(0.0356)	(0.0549)	(0.0915)	(0.0837)	(0.1562)	(0.0848)	(0.0714)	(0.1398)
ATT 2 quarters post	0.001	-0.0075	0.0477	0.0937	0.0092	0.0936	0.0775	0.0281	0.0075
	(0.0297)	(0.0341)	(0.0515)	(0.0772)	(0.0926)	(0.1166)	(0.0677)	(0.0847)	(0.1147)
ATT 3 quarters post	0.0184	0.0042	-0.0539	0.0977	-0.0666	-0.1817	0.0844	-0.0576	-0.1372
	(0.0316)	(0.0336)	(0.0622)	(0.0715)	(0.0914)	(0.1506)	(0.0606)	(0.0749)	(0.1296)
Treated Obs.	257	198	62	257	198	62	257	198	62
Avg. Untreated Obs.	112.2	125.5	150.5	112.2	125.5	150.5	112.2	125.5	150.5
First treatment									
ATT	0.1217**	0.0203	-0.0672	0.1548	-0.0362	-0.2079	0.0034	0.0104	-0.147
	(0.0505)	(0.0565)	(0.0635)	(0.1266)	(0.1579)	(0.1416)	(0.1231)	(0.1272)	(0.1296)
ATT 1 quarter post	0.1788***	0.1402**	0.0529	0.4861***	0.1668	0.2708	0.3158**	0.0611	0.2427
	(0.0489)	(0.0583)	(0.0581)	(0.1479)	(0.1536)	(0.197)	(0.1383)	(0.1394)	(0.1801)
ATT 2 quarters post	0.1163*	-0.0305	0.0181	0.3931**	-0.1115	-0.077	0.2431*	-0.1099	-0.1779
	(0.0622)	(0.0727)	(0.0517)	(0.1614)	(0.2077)	(0.1391)	(0.1332)	(0.1746)	(0.1557)
ATT 3 quarters post	0.0483	0.0144	-0.0906	0.0942	-0.2025	-0.2866	0.0039	-0.1873	-0.2229
	(0.0538)	(0.0729)	(0.0592)	(0.1386)	(0.1843)	(0.173)	(0.118)	(0.1553)	(0.1603)
Treated Obs.	63	58	39	63	58	39	63	58	39
Avg. Untreated Obs.	161	162.6	167.6	161	162.6	167.6	161	162.6	167.6

Outcome variables were log transformed.
Average number of untreated observations included in the matched control set of each treated observation.
Avg VC fund. reports the average amount of funding per VC deal per industry segment per quarter, in millions of U.S. dollars, considering only industry segments and quarters that received at least one VC deal.
Standard errors in parentheses were calculated through a block-bootstrapped procedure with 1,000 iterations. For details, see Imai et al. (2021, p.12).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First, we estimated a logistic model of treatment assignment, using for this a subset of data including values of the treatment variable ($treat_{i,t}$) and of all the covariates of interest ($\{ipo_{i,t-l}\}_{l=0}^{L}, \{ma_{i,t-l}\}_{l=0}^{L}, \{Y_{i,t-l}^{v}\}_{l=2}^{L}$) for all treated industry segments and their matched control industry segments. With these model estimates, we calculated predicted probabilities of treatment conditional on the covariates, which yielded the propensity scores for each treatment and matched control observation. We then assessed the level of similarity between the treatment and control observations, based on the differences in their calculated propensity scores.

6.4. Average effects of Big Tech start-up acquisitions

After we had obtained the weighted, average, counterfactual outcome $\widehat{Y_{i',t+F}^{v}}(treat_{i',t}=0, treat_{i',t-1}=0, \{treat_{i',t-l}\}_{l=2}^{L})$ for each treatment observation, based on matched observations of industry segments i', we calculated the differences-in-differences estimate $\widehat{\delta^{v}}(F,L) = Y_{i,t+F}^{v} - Y_{i,t-1}^{v} - (Y_{i',t+F}^{v} - Y_{i',t-1}^{v})$ for each of them, and then averaged the results across all industry segments. With this estimation approach, unit-specific fixed effects are ruled out in the difference of outcomes before and after each treatment time. In fact, as reported by Imai et al. (2021) (Theorem 1 at page 11), this DiD estimator is equivalent to the one obtained through a weighted, two-way fixed effects estimation.

This procedure yields the average treatment effect (ATT) estimates for the quarter of the treatment as well as for three leading quarters ($F = 3$) considering all treated industry segments and quarters. Detailed results for each estimate are provided in Table 6 for deals consummated worldwide, in the United States, and in Europe. However, it is possible that the effect of the first treatment in a given industry segment is different from the effect of the second, third, and fourth treatment in the same industry segment. For example, if a given industry segment received one or more Big Tech start-up acquisitions in quarters 8, 20, 23, and 37, there may be differences in the behavior of the outcome variables on and after the first (8), second (20), third (23), and fourth (37) treated quarter. To explore this possibility, we analyzed the effect on and after the very first treated quarter of each treated industry segment. The results are also reported in Table 6 for ease comparison with the results of the average effects obtained when all treatment units are considered. The effect on and after the second, third, etc. treated quarters was not explored in detail, although the detected pattern of first quarter and average effects suggests that there is a tapering off.

Figs. 3 and 4 provide graphical illustrations of the estimated average effects presented in Table 6 and their 90% confidence intervals considering all treatment units, as well as only the very first treatment unit of each industry segment, respectively. The choice of $F = 3$ was made to preserve coherence with the assumed carryover effect of three time-periods ($L = 3$) detailed in Section 00. Choosing a larger F would complicate the interpretation of the estimated ATTs, because it would increase the chances of treated industry segments receiving another treatment during the F lead time periods.

Using data of deals consummated worldwide, the results presented suggest statistically significant, positive, average effects of Big Tech start-up acquisitions on the total number of VC deals, total amount of VC funding, and average amount of VC funding per deal in treated industry segments. Higher average effects were found when we considered only the very first quarter of each industry segment that had received one or more treatments. Considering all treatments, an average increase of 6.37% [1.2%, 11.1%][13] on the total number of VC deals was found in the quarter of the treatment. The effects on the first, second, and third quarter after

[13] This and all other percentage values reported in brackets after the coefficients discussed in Section 6 refer to 90% confidence intervals.

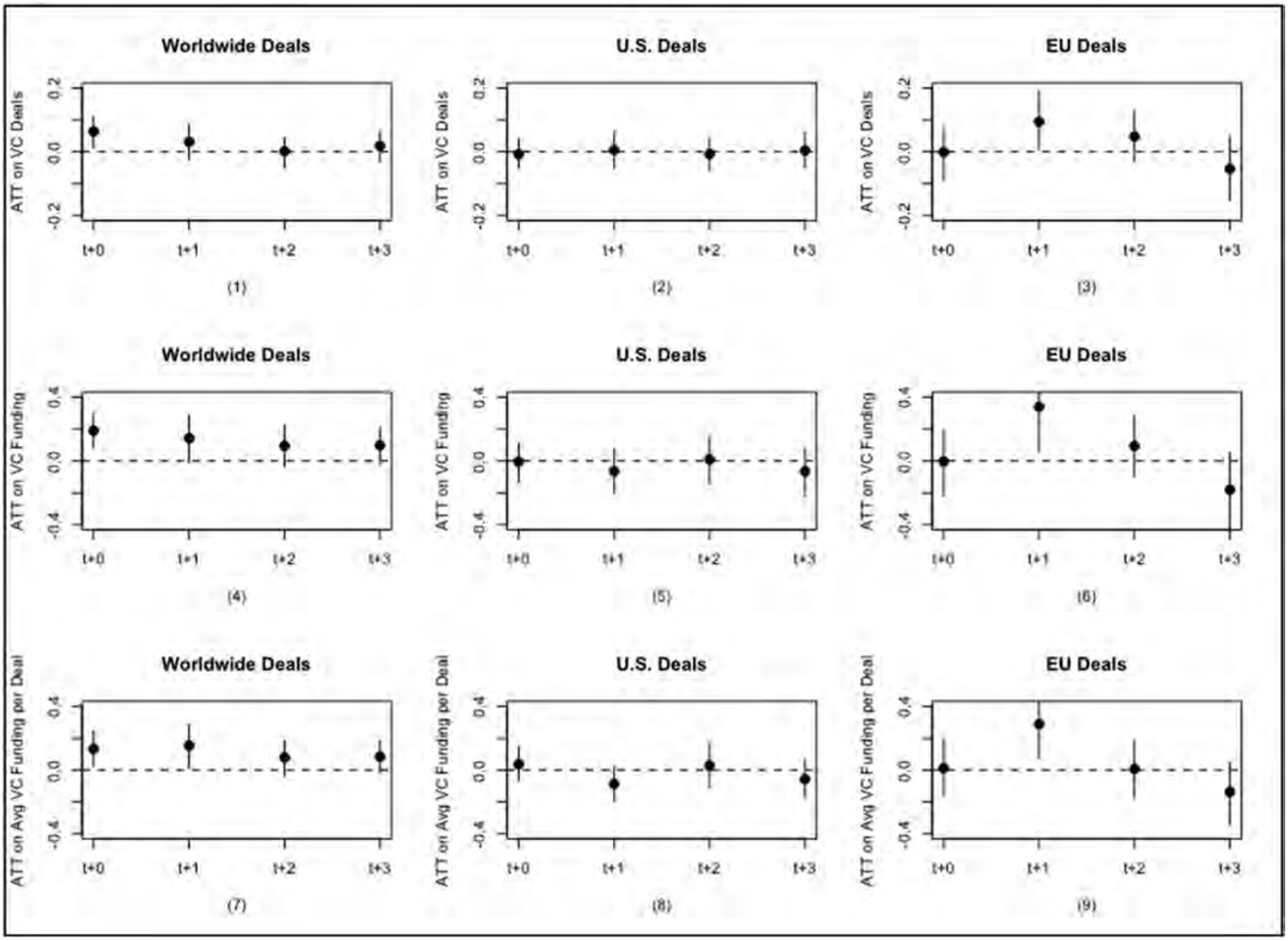

Fig. 3. Estimated effects of all treatment over time
90% confidence intervals based on block-bootstrapped standard errors using 1,000 iterations. For details, see Imai et al. (2021, p.12).

the treatment were not statistically different from zero. However, when we explored the average effects of the first treatment only, we found a 12.17% [3.96%, 20.57%], a 17.88% [9.81%, 25.68%], and a 11.63% [0.96%, 21.74%] increase in the number of VC deals in the quarter of the treatment and the two quarters following it, respectively.

When we examined the average effects of treatment on the amount of VC funding, we found a 18.92% [7.05%, 29.7%] increase in the quarter of the treatment when we analyzed all the treatments and a 48.61% [24.52%, 72.46%] and 39.31% [11.77%, 65.22%] increase in the two quarters following the quarter of the treatment, when we considered only the very first treated observation of each treated industry segments. These results are consistent with the ones reported in Section 5 and broadly support our earlier claim that a Big Tech start-up acquisition in a given industry segment produces a positive sign to venture capitalists that increases their interest in investing in start-ups of that industry segment. However, our dataset and empirical approach do not allow us to make conclusions about the type of positive sign Big Tech acquisitions gives to VC investors. An acquisition may signal increased market potential, the attractiveness of investment in complementary innovation activities, or a better prospect for a successful exit strategy in the future, as discussed in Section 2.3.

When we considered all treatment observations, we also found a statistically significant 13.32% [3.1%, 23.2%] and 15.26% [1.7%, 28.9%] increase in the average VC funding per deal per quarter in the quarter of an acquisition and the first quarter after it, respectively. When only the very first treatment was isolated, the average effects found were bigger: a 31.58% [6.2%, 52.23%] and a 24.31% [3.83%, 47.64%] increase, respectively. This shows that, although the average impact of an increment in the number of Big Tech start-up acquisitions is not statistically different from zero (as reported in Section 5), we can observe a statistically significant difference in the average VC funding per deal between treated and untreated industry segments after an acquisition.

An analysis of the effects of Big Tech acquisitions of U.S.-based start-ups on venture capital activity in the United States found no statistically significant average effects when we considered all treatment observations. As already discussed in the previous section, one explanation for these results may be the existence of highly dynamic venture capital activity in the United States. When only the very first treatment observations per industry segment were considered, a 14.02% [4.64%, 23.27%] average increase in the number of VC deals was found in the first quarter after a Big Tech acquisition of a U.S.-based start-up.

In contrast, when all treatment observations were considered in Europe, we found a 9.44% [0.5%, 18.1%] and a 33.97% [8.9%, 59,7%] increase in the number of VC deals and amount of VC funding in the first quarter following the quarter of an acquisition, respectively. Furthermore, we also found a statistically significant 28.82%

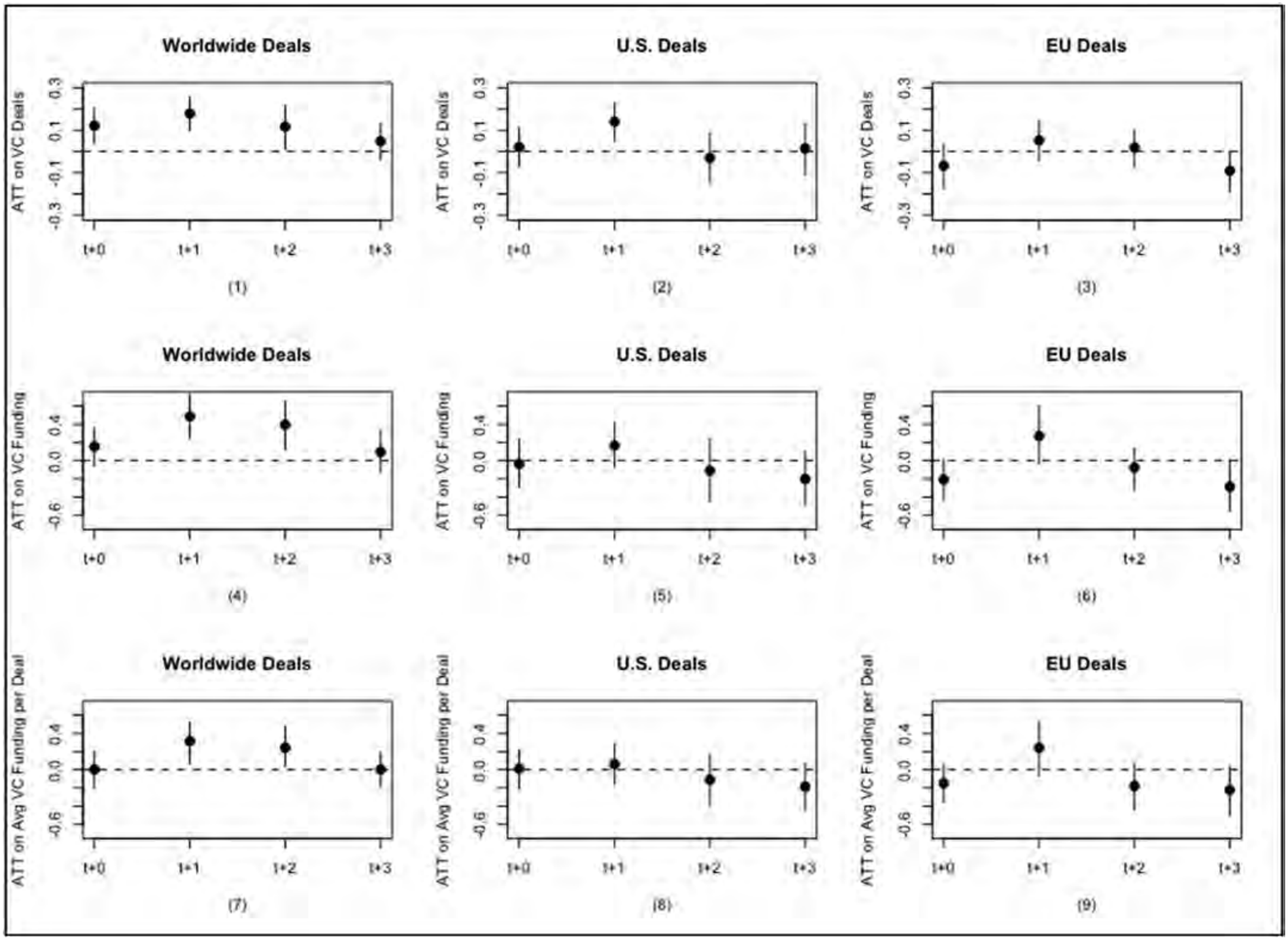

Fig. 4. Estimated effects of first treatment over time
90% confidence intervals based on block-bootstrapped standard errors using 1,000 iterations. For details, see Imai et al. (2021, p.12).

[5.96%, 51.50%] increase in the average amount of VC funding per deal in the first quarter after the treatment. These results align with the results of the two-way fixed effects Poisson estimation reported in Section 5. They challenge claims that Big Tech start-up acquisitions discourage VC investment in other European start-ups. It is interesting that no statistically significant effects were found in Europe when we considered only the very first treatment per industry segment. This suggests that not only the very first treatment, but also the following treatments affect the VC activity.

Finally, after a careful analysis of the results presented in Table 6 and illustrated in Figs. 3 and 4, one may argue that mostly insignificant results were found for the United States and Europe, although strong, positive, average effects of Big Tech start-up acquisitions on VC activity were found using the panel of deals that happened worldwide. This raises questions about which countries and regions could be driving the results found for the worldwide VC activity. One explanation for such results may be the existence of transregional effects of Big Tech start-up acquisitions on VC activity. Although our analysis for the United States and Europe explored only the effects on their respective VC activity of acquisitions that happened in these regions, it is plausible to expect that Big Tech acquisitions of start-ups based in the United States, China, or Latin America, for example, also affect VC activity in Europe, and vice-versa. This would contribute to an overall statistically significant effect found when industry segments are analyzed regardless of geographic breakdowns. To support such a claim of the existence of transregional effects of Big Tech start-up acquisitions, we have investigated the effects of U.S.-based acquisitions on VC activity in Europe. The results, reported in Fig. II.4 of Appendix II, confirm the existence of such transregional effects.

Our empirical analysis was based on thousands of venture capital deals, M&As, IPOs, and Big Tech start-up acquisitions consummated between 2010 and 2020 in more than 170 industry segments of the tech-related economy. It provides robust grounds for rejecting the existence of measurable negative effects of Big Tech start-up acquisitions on VC activity in these industry segments. Instead, we found statistically significant, positive effects. Our findings also show that when such positive effects exist, they persist primarily for a few months only and thus do not appear to have lasting impacts on the innovation incentives in the start-up ecosystem.

One potential objection to our results is the hypothesis that time-variant, informational shocks (e.g., a technological discovery or a new use-case for a technology) explain the findings. The econometrician does not observe such shocks, but the Big Techs and VC investors commonly observe them. They spur both acquisitions and VC activity and explain the strong association between Big Tech acquisitions and VC activity found in our empirical investigation. We believe that this hypothetical scenario is implausible for two reasons. First, it is very unlikely that these informational shocks happen frequently enough to explain the average, positive response of VC activity to Big Tech start-up acquisitions, especially when one considers that we analyzed 392 Big Tech start-up acquisitions.

Second, if one reasonably assumes that an M&A transaction (such as a Big Tech start-up acquisition) is more complex and time consuming than a VC investment, the effects of a common informational shock should first be perceived in the VC activity and then in the level of Big Tech start-up acquisitions, or simultaneously in the most optimistic scenario. But our empirical findings actually show that the opposite happens. Indeed, an overall analysis of the results reported in Tables 3–6 of Sections 5 and 6 allows us to conclude that that the effects in future VC activity (first to third quarter after the quarter of the acquisition) are bigger in magnitude and of higher statistical significance than the effects in the current VC activity (same quarter of the acquisition). In other words, if the average, positive effect on VC activity found is an average response to common, information shock that also caused Big Tech start-up acquisitions, the effect on Big Tech acquisitions should happen later than or even simultaneously to the effect on VC activity and not sooner.

7. Implications for competition policy and regulation

Our empirical investigation of the effects of Big Tech start-up acquisitions revealed nuanced patterns. Overall, we detected evidence of a positive, statistically significant increase in venture investment in the industry segments in which the acquired start-ups operate. During the ten-year period covered in our data, there are no, detectable, systematic negative effects on start-up funding. Thus, the empirical evidence suggests that, in a given industry segment, venture capital resources available to start-ups for innovation purposes increase after big-tech acquisitions. However, our analysis also shows that these effects are transitory and taper off over time. By the same token, our results do not suggest that promoting Big Tech start-up acquisitions is an instrument to advance lasting start-up innovation. To examine this issue, additional research would be required to investigate the long-term effects on innovation incentives.

These results challenge broad claims about the existence of short-term, negative impacts of Big Tech acquisitions on innovation, because of the creation of “kill zones” for start-ups. Our findings do not imply that such “kill zones” might not exist in specific cases, but there does not seem to be a systematic pattern across industry segments and extended periods. This should raise a flag of caution for current, competition policy discussions about imposing restrictions on the ability of Big Techs to acquire start-ups. It is difficult to establish a reliable, general, counterfactual of what might happen if broad competition policy restrictions were put in place. In this scenario, several effects could happen which cannot be explored with our dataset and empirical approach. It is plausible to expect that VC investors and entrepreneurs would have lower incentives to fund innovation due to diminished expectations of a successful exit of their investment by selling to a Big Tech (Cabral, 2021). It is also plausible to expect that, once Big Tech acquisitions are more difficult/rare, the effect of an acquisition on VC activity would be even higher, as it would signal a very strong interest of a Big Tech on an industry segment. We cannot provide supporting evidence for either of these scenarios, because our data is based on an observation period during which Big Tech start-up acquisitions were not made more difficult than any other M&A transaction. These ambiguities suggest that a case-by-case approach in which the evidence can be weighed carefully is superior to generic rules.

We believe that our findings complement the work by Gautier and Lamesch (2021) as well as by Callander and Matouschek (2021). However, based on our robust empirical findings, we draw more cautious conclusions for the appropriate role of competition policy. We find ourselves more in line with Federico et al. (2020), who propose that competition enforcers should analyze, in merger reviews, the past acquisitions of the incumbent platform seeking to acquire a nascent start-up to assess whether the platform has a pattern of killing-off acquired innovation projects or integrating them to enhance their products and services.

Big Techs’ acquisition strategies could have a median, socially positive outcome, because they foster innovation through increased venture capital activity. However, there are potential downsides because the mean effect of these activities may not be positive. This could happen if such acquisitions eliminate a “black swan” competitor, a start-up that might evolve into the “the next big digital platform.” Because start-ups are very dependent on a few Big Techs to succeed, it is plausible to assume that more competition in platform markets, such as social media, app stores, cloud services, etc., should not only bring more innovation to these markets, but also reduce the risk of investing in technology start-ups in other markets. Such a risk-reduction effect would have a positive impact on the entire innovation ecosystem by fostering more start-up creation and VC investment in many niches of the technology industry.

The adoption of regulatory or antitrust safeguards to avoid harm to innovation from Big Tech acquisitions in the long run is highly controversial. The current consumer standard used in antitrust in the United States often fails to capture such long-run effects. As Erik Hovenkamp emphasized in U.S. Department of Justice (2020), it should not be considered a competition policy issue that it is difficult to compete against the network effects and data analytical capabilities of the Big Tech companies. Nonetheless, competition policy and regulation should be concerned about the impact of Big Tech acquisitions on the trajectory of the market. Thus, the evidence needs to be compelling that an acquisition may kill or hinder the emergence of a start-up that might become a next Big Tech.

This suggests looking for a means other than broad prohibitions on acquisitions that can safeguard competition in the digital ecosystem. Gilbert (2021) suggests the consideration of a mix of antitrust enforcement and regulatory measures. For example, regulation could implement interoperability and data portability measures, even for small start-ups. This could create means for more start-ups to develop disruptive, innovative solutions that compete against big, incumbent players. In fact, well-funded start-ups with access to data and great AI tools might have good chances to succeed. They would ensure that the digital economy continues to generate high and long-lasting levels of investments and innovation to support economic development and welfare increases.

8. Conclusion

In this paper, we analyzed the effects of start-up acquisitions made by the Big Techs in the past decade on innovation incentives in different segments of the tech industry. Our results provide robust grounds for challenging claims about the existence of measurable, short-term, negative effects of Big Tech acquisitions on venture capital funding for innovation by start-up firms. After controlling for other factors that may affect VC activity, such as IPOs and other M&As, we found a statistically significant increase in the VC activity in response to Big Tech start-up acquisitions in different geographical breakdowns.

Our findings show, however, that such positive effects of Big Tech start-up acquisitions on VC activity persist for a few months only. Thus, they may not have long-term impacts on the innovation incentives in the start-up ecosystem. Aspects that deserve further investigation are potential spillover effects of Big Tech start-up acquisitions on industry segments adjacent to those selected by the Big Techs for the acquisitions. In fact, the observed increase in VC funding in industry segments that received such acquisitions may be a consequence of reallocation of funding from other similar industry segments. Important areas for future research include analyzing start-up creations and their death rates to investigate whether Big Tech acquisitions affect entrepreneurship and founders' willingness to start firms in the same industry segment, as well as their chances for success after a Big Tech acquisition in their industry segment.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

Tiago S. Prado: Conceptualization, Data curation, Formal analysis, Writing – original draft. **Johannes M. Bauer:** Conceptualization, Writing – review & editing, Funding acquisition.

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Appendix I. List of sector – industry – industry segment

Sector	Industry	Industry Segment
Internet	Internet Soft. & Serv.	Accounting & Finance
Internet	Internet Soft. & Serv.	Advertising Network or Exchange
Internet	Internet Soft. & Serv.	Advertising, Sales & Marketing
Internet	Internet Soft. & Serv.	Apparel & Accessories
Internet	Internet Soft. & Serv.	Application & Data Integration
Internet	Internet Soft. & Serv.	Asset & Financial Management & Trading
Internet	Internet Soft. & Serv.	Auto
Internet	Internet Soft. & Serv.	B2B Commerce
Internet	Internet Soft. & Serv.	Billing, Expense Management and Procurement
Internet	Internet Soft. & Serv.	Browser Software/Plugins
Internet	Internet Soft. & Serv.	Business Intelligence, Analytics & Performance Mgmt
Internet	Internet Soft. & Serv.	Collaboration & Project Management
Internet	Internet Soft. & Serv.	Compliance
Internet	Internet Soft. & Serv.	Conferencing & Communication
Internet	Internet Soft. & Serv.	Content Management
Internet	Internet Soft. & Serv.	Customer Relationship Management
Internet	Internet Soft. & Serv.	Data & Broadband
Internet	Internet Soft. & Serv.	Data & Document Management
Internet	Internet Soft. & Serv.	Data Storage
Internet	Internet Soft. & Serv.	Database Management
Internet	Internet Soft. & Serv.	Domain & SEO Services
Internet	Internet Soft. & Serv.	Education & Training
Internet	Internet Soft. & Serv.	Email
Internet	Internet Soft. & Serv.	Food & Grocery
Internet	Internet Soft. & Serv.	Gambling
Internet	Internet Soft. & Serv.	Gaming
Internet	Internet Soft. & Serv.	Government
Internet	Internet Soft. & Serv.	Green/Environmental
Internet	Internet Soft. & Serv.	HR & Workforce Management
Internet	Internet Soft. & Serv.	Health & Wellness
Internet	Internet Soft. & Serv.	Healthcare
Internet	Internet Soft. & Serv.	Information Providers & Portals
Internet	Internet Soft. & Serv.	Internet Service Provider
Internet	Internet Soft. & Serv.	Legal
Internet	Internet Soft. & Serv.	Manufacturing, Warehousing & Industrial
Internet	Internet Soft. & Serv.	Marketplace
Internet	Internet Soft. & Serv.	Monitoring & Security
Internet	Internet Soft. & Serv.	Multi-Product
Internet	Internet Soft. & Serv.	Multimedia & Graphics
Internet	Internet Soft. & Serv.	Music
Internet	Internet Soft. & Serv.	Music, Video, Books & Entertainment
Internet	Internet Soft. & Serv.	Networking & Connectivity
Internet	Internet Soft. & Serv.	News & Discussion
Internet	Internet Soft. & Serv.	Operating Systems & Utility
Internet	Internet Soft. & Serv.	Payments
Internet	Internet Soft. & Serv.	Personal & Professional Development
Internet	Internet Soft. & Serv.	Photo
Internet	Internet Soft. & Serv.	Real Estate
Internet	Internet Soft. & Serv.	Retail & Inventory
Internet	Internet Soft. & Serv.	Scientific, Engineering
Internet	Internet Soft. & Serv.	Search
Internet	Internet Soft. & Serv.	Social
Internet	Internet Soft. & Serv.	Sporting Goods
Internet	Internet Soft. & Serv.	Sports
Internet	Internet Soft. & Serv.	Supply Chain & Logistics
Internet	Internet Soft. & Serv.	Testing
Internet	Internet Soft. & Serv.	Travel
Internet	Internet Soft. & Serv.	Video
Internet	Internet Soft. & Serv.	Web Development
Internet	Internet Soft. & Serv.	Website hosting
Internet	Internet Soft. & Serv.	eCommerce enablement
Internet	eCommerce	Accounting & Finance
Internet	eCommerce	Advertising, Sales & Marketing
Internet	eCommerce	Apparel & Accessories
Internet	eCommerce	Asset & Financial Management & Trading
Internet	eCommerce	Auction & Classifieds
Internet	eCommerce	Auto
Internet	eCommerce	B2B Commerce
Internet	eCommerce	Collaboration & Project Management
Internet	eCommerce	Comparison Shopping
Internet	eCommerce	Computer & Software
Internet	eCommerce	Digital Goods
Internet	eCommerce	Discount
Internet	eCommerce	Education & Training
Internet	eCommerce	Electronics & Appliances
Internet	eCommerce	Email
Internet	eCommerce	Events & Ticketing
Internet	eCommerce	Food & Grocery
Internet	eCommerce	Gasoline

(continued on next page)

Internet	eCommerce	HR & Workforce Management
Internet	eCommerce	Home Furnishings & Improvement
Internet	eCommerce	Jewelry
Internet	eCommerce	Marketplace
Internet	eCommerce	Multi-Product
Internet	eCommerce	Music, Video, Books & Entertainment
Internet	eCommerce	Office Products
Internet	eCommerce	Other Retail
Internet	eCommerce	Pharmacies
Internet	eCommerce	Retail & Inventory
Internet	eCommerce	Social
Internet	eCommerce	Sporting Goods
Internet	eCommerce	Toys & Games
Internet	eCommerce	Travel
Internet	eCommerce	Travel (internet)
Internet	eCommerce	eCommerce enablement
Mobile & Telecom	Mobile Commerce	Accounting & Finance
Mobile & Telecom	Mobile Commerce	Apparel & Accessories
Mobile & Telecom	Mobile Commerce	Auction & Classifieds
Mobile & Telecom	Mobile Commerce	Auto
Mobile & Telecom	Mobile Commerce	B2B Commerce
Mobile & Telecom	Mobile Commerce	Comparison Shopping
Mobile & Telecom	Mobile Commerce	Customer Relationship Management
Mobile & Telecom	Mobile Commerce	Digital Goods
Mobile & Telecom	Mobile Commerce	Discount
Mobile & Telecom	Mobile Commerce	Electronics & Appliances
Mobile & Telecom	Mobile Commerce	Food & Grocery
Mobile & Telecom	Mobile Commerce	Gaming
Mobile & Telecom	Mobile Commerce	Gasoline
Mobile & Telecom	Mobile Commerce	HR & Workforce Management
Mobile & Telecom	Mobile Commerce	Home Furnishings & Improvement
Mobile & Telecom	Mobile Commerce	Jewelry
Mobile & Telecom	Mobile Commerce	Marketplace
Mobile & Telecom	Mobile Commerce	Mobile Commerce enablement
Mobile & Telecom	Mobile Commerce	Multi-Product
Mobile & Telecom	Mobile Commerce	Music, Video, Books & Entertainment
Mobile & Telecom	Mobile Commerce	Other Retail
Mobile & Telecom	Mobile Commerce	Payments
Mobile & Telecom	Mobile Commerce	Pharmacies
Mobile & Telecom	Mobile Commerce	Photo
Mobile & Telecom	Mobile Commerce	Supply Chain & Logistics
Mobile & Telecom	Mobile Commerce	Travel (mobile)
Mobile & Telecom	Mobile Soft. & Serv.	Accounting & Finance
Mobile & Telecom	Mobile Soft. & Serv.	Advertising Network or Exchange
Mobile & Telecom	Mobile Soft. & Serv.	Advertising, Sales & Marketing
Mobile & Telecom	Mobile Soft. & Serv.	Application & Data Integration
Mobile & Telecom	Mobile Soft. & Serv.	Application Development
Mobile & Telecom	Mobile Soft. & Serv.	Asset & Financial Management & Trading
Mobile & Telecom	Mobile Soft. & Serv.	Billing, Expense Management and Procurement

(continued on next page)

Mobile & Telecom	Mobile Soft. & Serv.	Browser Software/Plugins
Mobile & Telecom	Mobile Soft. & Serv.	Business Intelligence, Analytics & Performance Mgmt
Mobile & Telecom	Mobile Soft. & Serv.	Collaboration & Project Management
Mobile & Telecom	Mobile Soft. & Serv.	Compliance
Mobile & Telecom	Mobile Soft. & Serv.	Conferencing & Communication
Mobile & Telecom	Mobile Soft. & Serv.	Content Management
Mobile & Telecom	Mobile Soft. & Serv.	Customer Relationship Management
Mobile & Telecom	Mobile Soft. & Serv.	Data & Document Management
Mobile & Telecom	Mobile Soft. & Serv.	Database Management
Mobile & Telecom	Mobile Soft. & Serv.	Education & Training
Mobile & Telecom	Mobile Soft. & Serv.	Email
Mobile & Telecom	Mobile Soft. & Serv.	Food & Grocery
Mobile & Telecom	Mobile Soft. & Serv.	Gambling
Mobile & Telecom	Mobile Soft. & Serv.	Gaming
Mobile & Telecom	Mobile Soft. & Serv.	Government
Mobile & Telecom	Mobile Soft. & Serv.	Green/Environmental
Mobile & Telecom	Mobile Soft. & Serv.	HR & Workforce Management
Mobile & Telecom	Mobile Soft. & Serv.	Health & Wellness
Mobile & Telecom	Mobile Soft. & Serv.	Healthcare
Mobile & Telecom	Mobile Soft. & Serv.	Information Providers & Portals
Mobile & Telecom	Mobile Soft. & Serv.	Legal
Mobile & Telecom	Mobile Soft. & Serv.	Location-Based & Navigation
Mobile & Telecom	Mobile Soft. & Serv.	Manufacturing, Warehousing & Industrial
Mobile & Telecom	Mobile Soft. & Serv.	Multi-Product
Mobile & Telecom	Mobile Soft. & Serv.	Multimedia & Graphics
Mobile & Telecom	Mobile Soft. & Serv.	Music
Mobile & Telecom	Mobile Soft. & Serv.	Networking & Connectivity
Mobile & Telecom	Mobile Soft. & Serv.	News & Discussion
Mobile & Telecom	Mobile Soft. & Serv.	Operating Systems & Utility
Mobile & Telecom	Mobile Soft. & Serv.	Payments
Mobile & Telecom	Mobile Soft. & Serv.	Personal & Professional Development
Mobile & Telecom	Mobile Soft. & Serv.	Photo
Mobile & Telecom	Mobile Soft. & Serv.	Point of Sale
Mobile & Telecom	Mobile Soft. & Serv.	Real Estate
Mobile & Telecom	Mobile Soft. & Serv.	Scientific, Engineering
Mobile & Telecom	Mobile Soft. & Serv.	Search
Mobile & Telecom	Mobile Soft. & Serv.	Security
Mobile & Telecom	Mobile Soft. & Serv.	Social
Mobile & Telecom	Mobile Soft. & Serv.	Sports
Mobile & Telecom	Mobile Soft. & Serv.	Storage & Systems Management
Mobile & Telecom	Mobile Soft. & Serv.	Supply Chain & Logistics
Mobile & Telecom	Mobile Soft. & Serv.	Testing
Mobile & Telecom	Mobile Soft. & Serv.	Travel
Mobile & Telecom	Mobile Soft. & Serv.	Video
Mobile & Telecom	Mobile Soft. & Serv.	eCommerce enablement

Note: The classification of start-ups per sector, industry, and subindustry was performed by CB Insights, which has implemented this very detailed and consistent classification system throughout the years based on the description of the main activities of each start-up included in the dataset. Each start-up was classified in a unique sector-industry-subindustry triad.

Appendix II

App para, Figs. II.1–II.4, Tables II.1–II.4

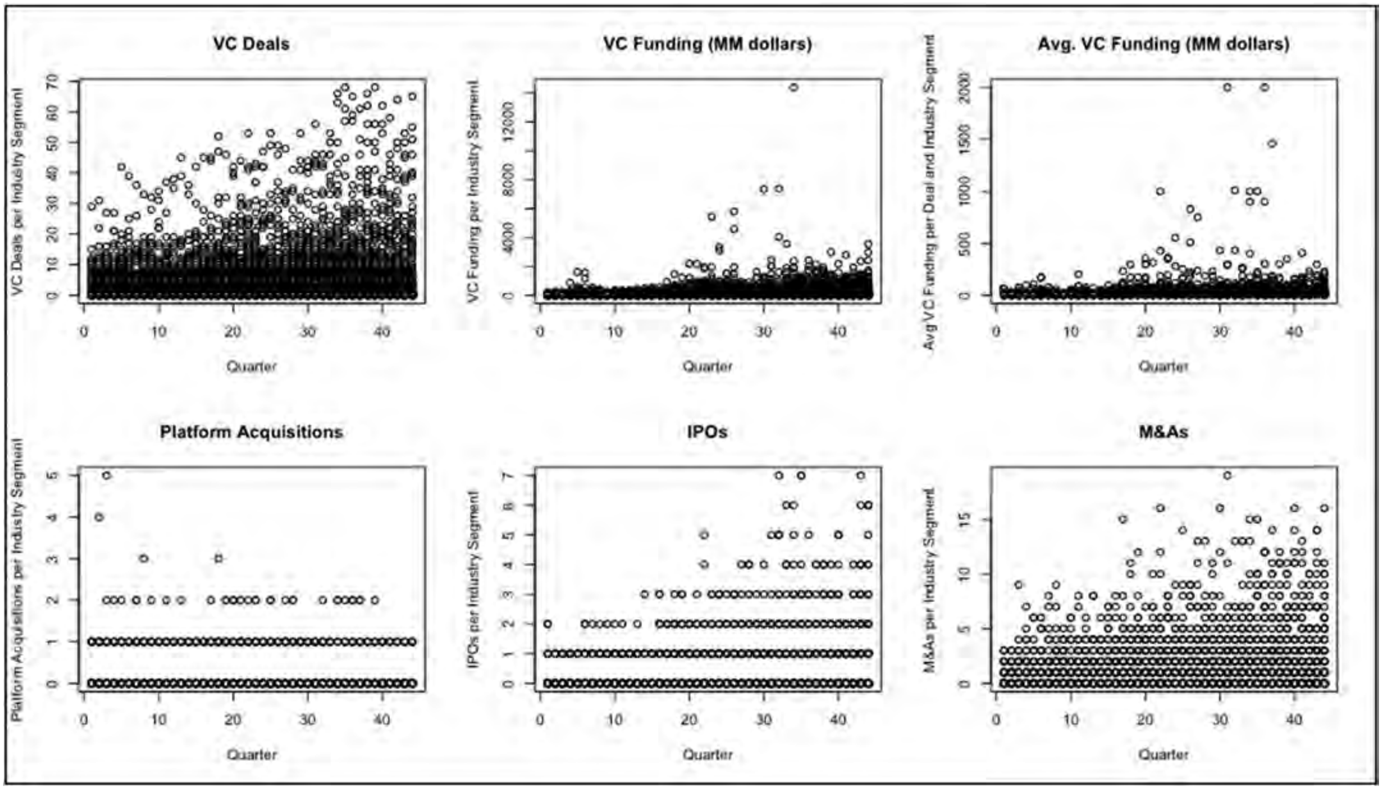

Fig. II.1. Distribution of variables per quarter for worldwide deals.

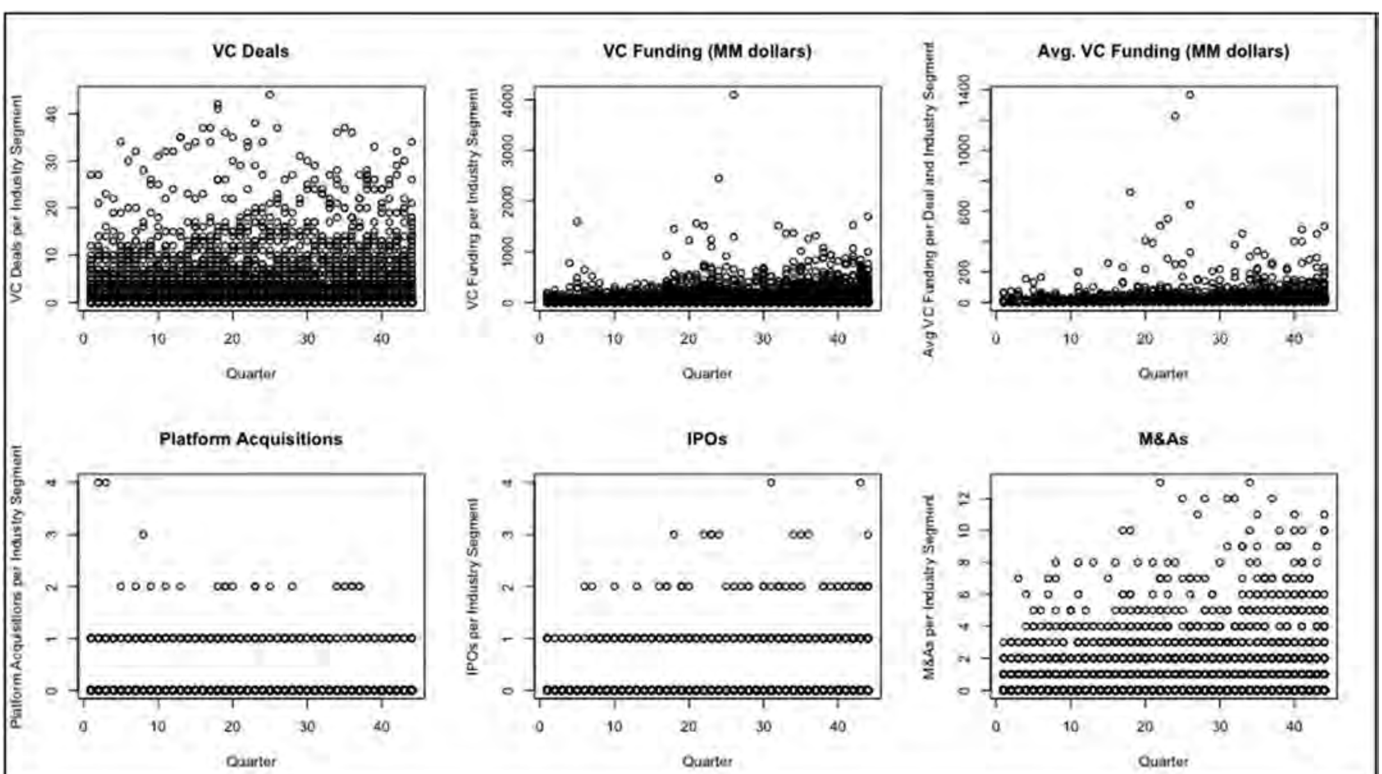

Fig. II.2. Distribution of variables per quarter for U.S. deals.

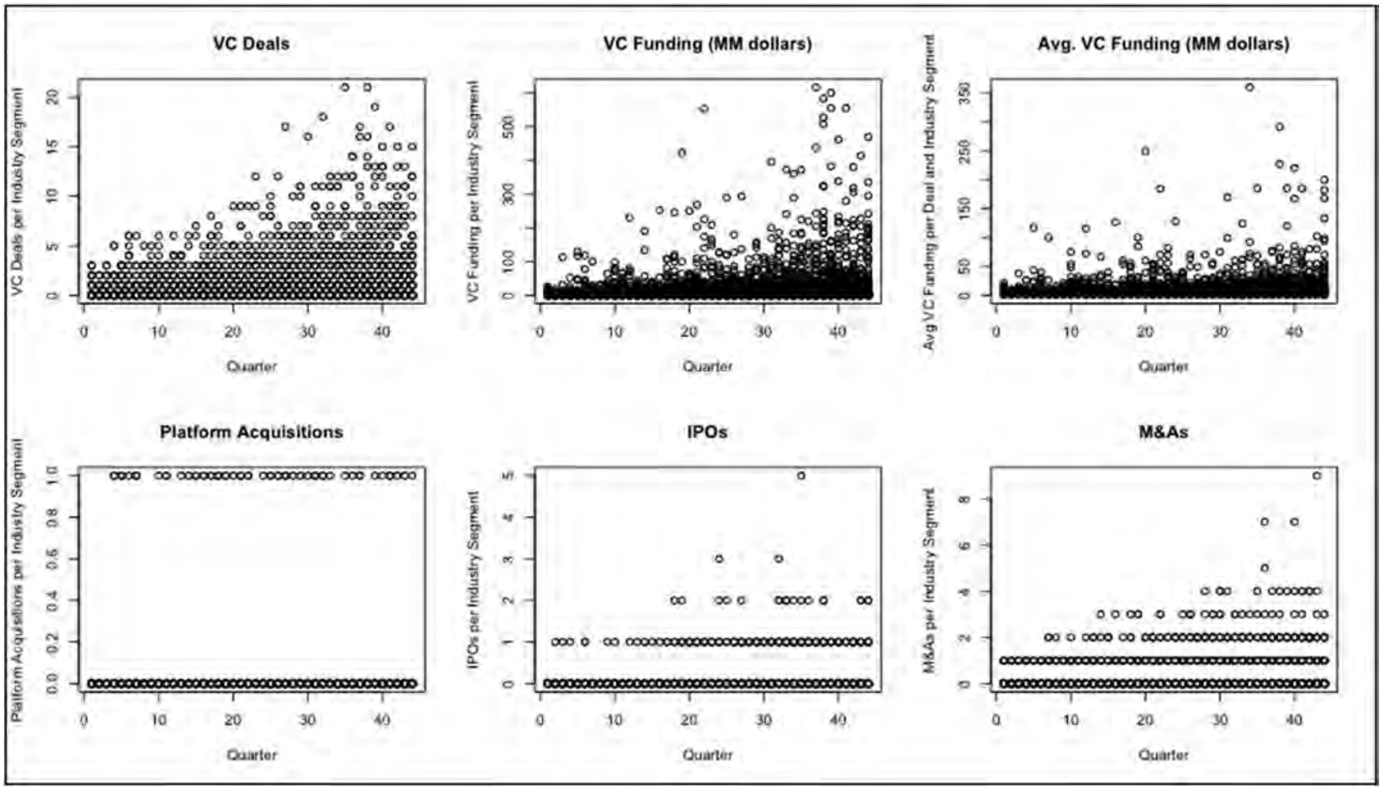

Fig. II.3. Distribution of variables per quarter for European deals.

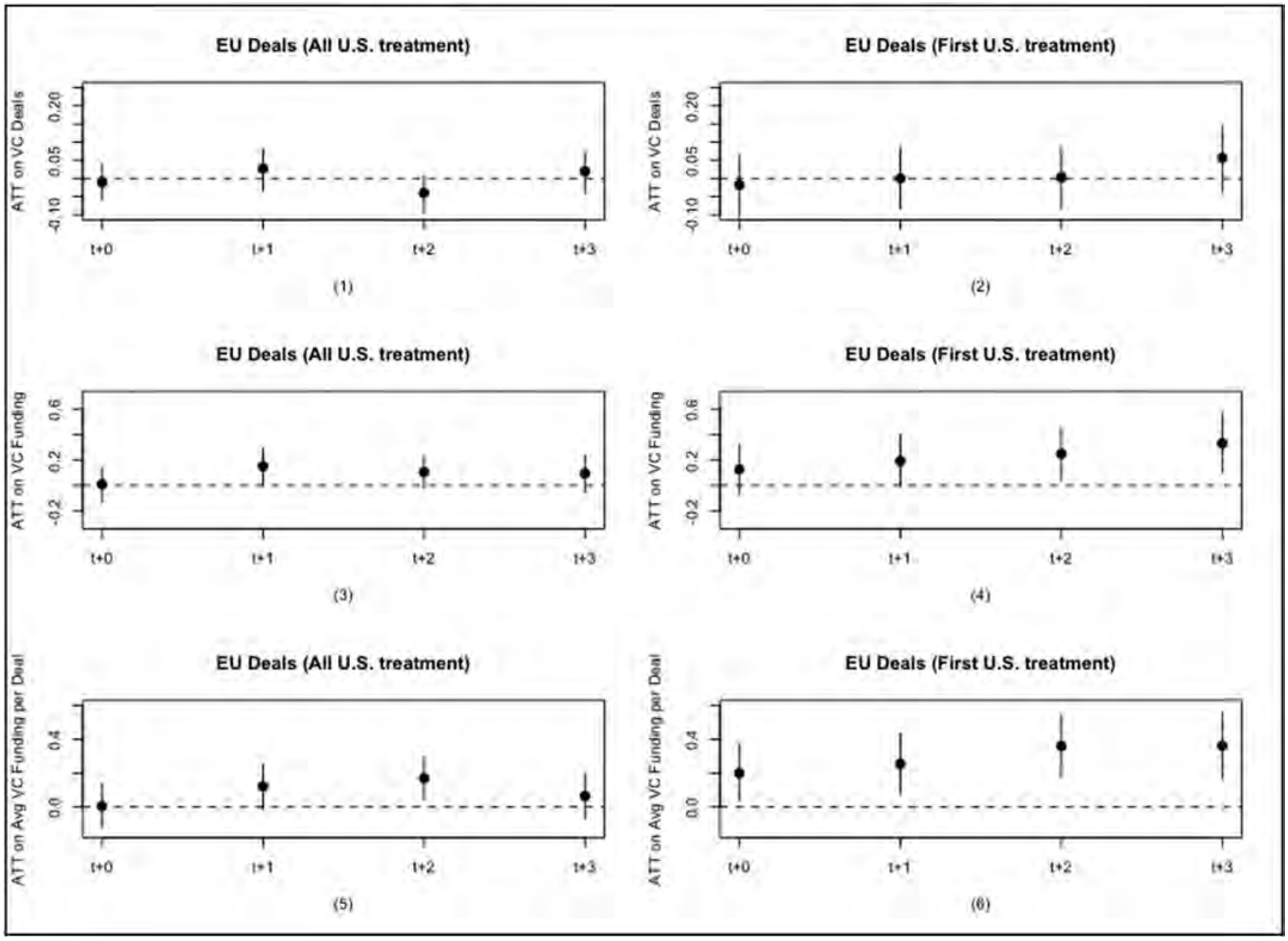

Fig. II.4. Estimated average effects of Big Tech acquisitions of U.S.-based start-ups on VC activity in Europe
90% confidence intervals based on block-bootstrapped standard errors using 1,000 iterations. For details, see Imai et al. (2021, p.12).
Plots (1), (3), and (5) graphically illustrate the estimated average effects of Big Tech acquisition of U.S.-based start-ups on the number of VC deals, amount of VC funding, and average VC funding per deal per quarter in Europe, for the quarter of the acquisitions and the three quarters following it, considering all treatment observations.
Plots (2), (4), and (6) graphically illustrate the estimated average effects of Big Tech acquisition of U.S.-based start-ups on the number of VC deals, amount of VC funding, and average VC funding per deal per quarter in Europe, for the quarter of the acquisitions and the three quarters following it, considering only the very first treatment observations of each industry segment.

Table II.1
Distribution of VC activity, platform acquisitions, IPOs, and M&As per region.

Continent	North Amer.	Europe	Asia	South Amer.	Africa	Oceania	All
Variables							
VC deals	17934	5342	8185	407	139	360	32367
VC funding	345.4	72.4	316.2	9.6	1.8	3.9	749.3
Avg. VC funding	19.3	13.6	38.6	23.7	12.7	10.7	23.2
Plat. Acqui.	312	66	13	0	0	1	392
IPOs	496	260	618	10	4	59	1447
M&As	4147	1118	778	78	4	24	6149

VC funding is reported in billions of U.S. dollars.
Avg VC fund. reports the average amount of funding per VC deal, in millions of U.S. dollars.

Table II.2
Detailed results of the two-way fixed effects Poisson estimation - Worldwide.

Outcome Var.	: VC Deals				| VC Fund |				Avg. VC Fund			
	(1)	(2)	(3)	(3.F)	(4)	(5)	(6)	(6.F)	(7)	(8)	(9)	(9.F)
main plat	0.0298	0.0183	0.0229	0.0240	0.0279	0.0187	0.0197	0.0331	0.0403	0.0355	0.00275	0.0134
	(0.0317)	(0.0318)	(0.0279)	(0.0281)	(0.0762)	(0.0759)	(0.0751)	(0.0725)	(0.0843)	(0.0859)	(0.0929)	(0.0917)
L.plat	0.0627	0.0509	0.0474*	0.0459*	0.0734	0.0698	0.0712	0.0801	0.0962	0.0977	0.0457	0.0470
	(0.0411)	(0.0397)	(0.0259)	(0.0251)	(0.0725)	(0.0792)	(0.0781)	(0.0799)	(0.0813)	(0.0843)	(0.0849)	(0.0860)
L2.plat	0.0812**	0.0711**	0.0704***	0.0679***	0.195*	0.198*	0.198*	0.195*	0.103	0.114	0.0803	0.0842
	(0.0346)	(0.0338)	(0.0197)	(0.0200)	(0.113)	(0.110)	(0.110)	(0.106)	(0.0915)	(0.0927)	(0.0963)	(0.0971)
L3.plat	0.0668**	0.0616*	0.0610***	0.0577***	0.148*	0.119	0.117	0.133	0.0604	0.0456	0.0596	0.0613
	(0.0309)	(0.0323)	(0.0207)	(0.0212)	(0.0844)	(0.0839)	(0.0829)	(0.0814)	(0.0607)	(0.0654)	(0.0715)	(0.0754)
F.plat				0.0111				0.125				0.0531
				(0.0268)				(0.0990)				(0.0989)
ipo		0.0240***	-0.00192	-0.00272		0.00610	0.00424	0.000770		0.00336	0.0233	0.0325
		(0.00824)	(0.00864)	(0.00914)		(0.0331)	(0.0346)	(0.0411)		(0.0526)	(0.0519)	(0.0559)
m&a		0.0133**	-0.00555	-0.00504		-0.00398	-0.00445	-0.00552		0.00313	0.000115	0.00239
		(0.00623)	(0.00445)	(0.00441)		(0.0218)	(0.0209)	(0.0201)		(0.0232)	(0.0226)	(0.0239)
L.ipo		0.00504	-0.0223**	-0.0264***		0.0504*	0.0503*	0.0406		0.0267	0.0276	0.0349
		(0.0125)	(0.00993)	(0.00982)		(0.0272)	(0.0276)	(0.0296)		(0.0374)	(0.0387)	(0.0403)
L2.ipo		0.0115	-0.0147**	-0.0136*		0.00879	0.00677	0.00494		-0.0151	0.0120	0.0113
		(0.00850)	(0.00716)	(0.00765)		(0.0163)	(0.0167)	(0.0164)		(0.0313)	(0.0227)	(0.0234)
L3.ipo		0.00330	-0.0201*	-0.0210*		0.00587	0.00518	0.0152		0.0324	-0.000486	0.00883
		(0.0153)	(0.0115)	(0.0119)		(0.0285)	(0.0289)	(0.0289)		(0.0445)	(0.0366)	(0.0368)
F.ipo				0.00118				0.0398*				0.0227
				(0.00873)				(0.0241)				(0.0309)
L.m&a		0.00853	-0.0103**	-0.0101**		-0.00762	-0.00744	-0.00620		-0.0175	-0.00458	-0.00609
		(0.00524)	(0.00442)	(0.00448)		(0.0139)	(0.0136)	(0.0160)		(0.0209)	(0.0200)	(0.0212)
L2.m&a		0.00325	-0.0143***	-0.0158***		0.0148	0.0149	0.0111		-0.00562	-0.00807	-0.00950
		(0.00618)	(0.00419)	(0.00402)		(0.0118)	(0.0120)	(0.0127)		(0.0154)	(0.0162)	(0.0174)
L3.m&a		-0.00128	-0.0166***	-0.0166***		0.0257	0.0251	0.0119		0.0257	0.0257	0.0218
		(0.00613)	(0.00463)	(0.00455)		(0.0182)	(0.0186)	(0.0215)		(0.0219)	(0.0200)	(0.0233)
F.m&a				0.00125				-0.00399				-0.0275
				(0.00320)				(0.0268)				(0.0266)
L.vcdeals			0.0134***	0.0140***								
			(0.00157)	(0.00160)								
L2.vcdeas			0.0107***	0.00985***								
			(0.00175)	(0.00167)								
L3.vcdeas			0.00701***	0.00672***								
			(0.00186)	(0.00188)								
L4.vcdeas			0.00573***	0.00568***								
			(0.00175)	(0.00184)								
L.vcfund							0.0000313	0.0000192				
							(0.0000432)	(0.0000442)				
L.avg_vcfund											-0.00104***	-0.00117***
											(0.000315)	(0.000316)
N	7093	7093	6920	6747	7093	7093	7093	6920	4408	4408	3787	3688

Standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table II.3
Detailed results of the two-way fixed effects Poisson estimation - U.S.

Outcome Var.:	VC Deals				| VC Fund |				Avg. VC Fund			
	(1)	(2)	(3)	(3.F)	(4)	(5)	(6)	(6.F)	(7)	(8)	(9)	(9.F)
main												
plat	-0.0951	-0.0986	-0.0993	-0.168	-0.225	-0.264	-0.259	-0.334*	0.106	0.0940	0.0510	0.00536
	(0.120)	(0.120)	(0.123)	(0.139)	(0.168)	(0.169)	(0.167)	(0.183)	(0.272)	(0.263)	(0.319)	(0.337)
L.plat	0.0646	0.0665	0.110	0.0929	0.680*	0.659*	0.667*	0.656*	0.478*	0.475*	0.0198	-0.0415
	(0.119)	(0.119)	(0.110)	(0.123)	(0.359)	(0.374)	(0.370)	(0.372)	(0.248)	(0.258)	(0.219)	(0.213)
L2.plat	0.236*	0.248*	0.310**	0.265*	0.651**	0.666**	0.657**	0.637*	0.563	0.588	-0.0739	-0.115
	(0.143)	(0.149)	(0.153)	(0.137)	(0.302)	(0.312)	(0.316)	(0.329)	(0.398)	(0.400)	(0.340)	(0.354)
L3 .plat	-0.104	-0.0964	-0.0720	-0.130	0.221	0.248	0.241	0.222	0.417	0.445	-0.399	-0.446
	(0.140)	(0.147)	(0.143)	(0.135)	(0.377)	(0.382)	(0.382)	(0.401)	(0.467)	(0.465)	(0.450)	(0.516)
F.plat				-0.176				-0.341				-0.421
				(0.177)				(0.223)				(0.391)
ipo		0.0470	0.00403	-0.0230		0.120*	0.117*	0.138**		0.122	0.121	0.170*
		(0.0306)	(0.0285)	(0.0291)		(0.0654)	(0.0667)	(0.0614)		(0.0872)	(0.0861)	(0.0879)
m&a		0.00887	-0.0164	-0.0176		0.0342	0.0312	0.0130		0.00457	0.0422	0.0348
		(0.0177)	(0.0147)	(0.0160)		(0.0392)	(0.0409)	(0.0363)		(0.0532)	(0.0638)	(0.0609)
L.ipo		0.0419	0.0160	-0.0113		0.129	0.125	0.147		0.0368	0.105	0.147
		(0.0260)	(0.0269)	(0.0280)		(0.106)	(0.100)	(0.0924)		(0.0977)	(0.112)	(0.108)
L2.ipo		0.0317	-0.000109	-0.00562		0.0273	0.0170	0.000490		0.0279	-0.0165	-0.00517
		(0.0295)	(0.0254)	(0.0274)		(0.0643)	(0.0656)	(0.0655)		(0.0858)	(0.101)	(0.0949)
L3.ipo		0.000371	-0.0394	-0.0545		0.0827	0.0775	0.0662		-0.00631	0.0949	0.0784
		(0.0432)	(0.0372)	(0.0418)		(0.0628)	(0.0622)	(0.0592)		(0.106)	(0.0736)	(0.0652)
F.ipo				-0.0494				0.0543				0.146*
				(0.0468)				(0.0652)				(0.0836)
L.m&a		-0.00963	-0.0382**	-0.0480***		-0.0361	-0.0410	-0.0133		-0.0230	0.000253	0.0135
		(0.0147)	(0.0167)	(0.0179)		(0.0346)	(0.0356)	(0.0510)		(0.0471)	(0.0529)	(0.0585)
L2.m&a		-0.00104	-0.0398**	-0.0294*		-0.0348	-0.0391	-0.0313		-0.0365	-0.00436	-0.0112
		(0.0167)	(0.0162)	(0.0155)		(0.0383)	(0.0389)	(0.0378)		(0.0459)	(0.0427)	(0.0445)
L3.m&a		-0.000834	-0.0328**	-0.0522***		-0.0261	-0.0312	-0.00572		-0.0268	-0.0464	-0.0253
		(0.0173)	(0.0157)	(0.0178)		(0.0270)	(0.0279)	(0.0348)		(0.0374)	(0.0291)	(0.0442)
F.m&a				0.0346*				-0.0156				-0.0482
				(0.0200)				(0.0316)				(0.0502)
L. vcdeals			0.0155*	0.0162*								
			(0.00825)	(0.00859)								
L2.vcdeas			0.0374***	0.0386***								
			(0.0100)	(0.00928)								
L3.vcdeas			0.0323***	0.0321***								
			(0.00758)	(0.00783)								
L.vcfund.							0.000305	0.000296				
							(0.000393)	(0.000372)				
L2.vcfund							0.000158	0.000188				
							(0.000469)	(0.000502)				
L3.vcfund							0.000186	0.000104				
							(0.000283)	(0.000350)				
L.avg vcfund											-0.00375**	-0.00510***
											(0.00179)	(0.00196)
L2.avg vcfund											-0.00232	-0.00261
											(0.00161)	(0.00160)
L3.avg vcfund											-0.00189	-0.00417***
											(0.00200)	(0.00138)
N	5494	5494	5494	5280	5494	5494	5494	5280	2195	2195	82 3	787
L3.avg_vcfund											0.00209***	0.00216***
											(0.000552)	(0.000505)
L4.avg_vcfund											-0.00113*	-0.00126**
											(0.000617)	(0.000608)
L5.avg_vcfund											-0.000273	-0.000370
											(0.000621)	(0.000670)
N	6519	6519	6201	6042	6519	6519	6201	6042	3626	3626	2134	2082

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table II.4
Detailed results of the two-way fixed effects Poisson estimation - Europe.

Outcome Var.:	VC Deals				| VC Fund |				Avg. VC Fund			
	(1)	(2)	(3)	(3.F)	(4)	(5)	(6)	(6.F)	(7)	(8)	(9)	(9.F)
main												
plat	-0.0951	-0.0986	-0.0993	-0.168	-0.225	-0.264	-0.259	-0.334*	0.106	0.0940	0.0510	0.00536
	(0.120)	(0.120)	(0.123)	(0.139)	(0.168)	(0.169)	(0.167)	(0.183)	(0.272)	(0.263)	(0.319)	(0.337)
L.plat	0.0646	0.0665	0.110	0.0929	0.680*	0.659*	0.667*	0.656*	0.478*	0.475*	0.0198	-0.0415
	(0.119)	(0.119)	(0.110)	(0.123)	(0.359)	(0.374)	(0.370)	(0.372)	(0.248)	(0.258)	(0.219)	(0.213)
L2.plat	0.236*	0.248*	0.310**	0.265*	0.651**	0.666**	0.657**	0.637*	0.563	0.588	-0.0739	-0.115
	(0.143)	(0.149)	(0.153)	(0.137)	(0.302)	(0.312)	(0.316)	(0.329)	(0.398)	(0.400)	(0.340)	(0.354)
L3 .plat	-0.104	-0.0964	-0.0720	-0.130	0.221	0.248	0.241	0.222	0.417	0.445	-0.399	-0.446
	(0.140)	(0.147)	(0.143)	(0.135)	(0.377)	(0.382)	(0.382)	(0.401)	(0.467)	(0.465)	(0.450)	(0.516)
F.plat				-0.176 (0.177)				-0.341 (0.223)				-0.421 (0.391)
ipo		0.0470	0.00403	-0.0230		0.120*	0.117*	0.138**		0.122	0.121	0.170*
		(0.0306)	(0.0285)	(0.0291)		(0.0654)	(0.0667)	(0.0614)		(0.0872)	(0.0861)	(0.0879)
m&a		0.00887	-0.0164	-0.0176		0.0342	0.0312	0.0130		0.00457	0.0422	0.0348
		(0.0177)	(0.0147)	(0.0160)		(0.0392)	(0.0409)	(0.0363)		(0.0532)	(0.0638)	(0.0609)
L.ipo		0.0419	0.0160	-0.0113		0.129	0.125	0.147		0.0368	0.105	0.147
		(0.0260)	(0.0269)	(0.0280)		(0.106)	(0.100)	(0.0924)		(0.0977)	(0.112)	(0.108)
L2.ipo		0.0317	-0.000109	-0.00562		0.0273	0.0170	0.000490		0.0279	-0.0165	-0.00517
		(0.0295)	(0.0254)	(0.0274)		(0.0643)	(0.0656)	(0.0655)		(0.0858)	(0.101)	(0.0949)
L3.ipo		0.000371	-0.0394	-0.0545		0.0827	0.0775	0.0662		-0.00631	0.0949	0.0784
		(0.0432)	(0.0372)	(0.0418)		(0.0628)	(0.0622)	(0.0592)		(0.106)	(0.0736)	(0.0652)
F.ipo				-0.0494 (0.0468)				0.0543 (0.0652)				0.146* (0.0836)
L.m&a		-0.00963	-0.0382**	-0.0480***		-0.0361	-0.0410	-0.0133		-0.0230	0.000253	0.0135
		(0.0147)	(0.0167)	(0.0179)		(0.0346)	(0.0356)	(0.0510)		(0.0471)	(0.0529)	(0.0585)
L2.m&a		-0.00104	-0.0398**	-0.0294*		-0.0348	-0.0391	-0.0313		-0.0365	-0.00436	-0.0112
		(0.0167)	(0.0162)	(0.0155)		(0.0383)	(0.0389)	(0.0378)		(0.0459)	(0.0427)	(0.0445)
L3.m&a		-0.000834	-0.0328**	-0.0522***		-0.0261	-0.0312	-0.00572		-0.0268	-0.0464	-0.0253
		(0.0173)	(0.0157)	(0.0178)		(0.0270)	(0.0279)	(0.0348)		(0.0374)	(0.0291)	(0.0442)
F.m&a				0.0346* (0.0200)				-0.0156 (0.0316)				-0.0482 (0.0502)
L. vcdeals			0.0155* (0.00825)	0.0162* (0.00859)								
L2.vcdeas			0.0374*** (0.0100)	0.0386*** (0.00928)								
L3.vcdeas			0.0323*** (0.00758)	0.0321*** (0.00783)								
L.vcfund.							0.000305 (0.000393)	0.000296 (0.000372)				
L2.vcfund							0.000158 (0.000469)	0.000188 (0.000502)				
L3.vcfund							0.000186 (0.000283)	0.000104 (0.000350)				
L.avg vcfund											-0.00375**	-0.00510***
											(0.00179)	(0.00196)
L2.avg vcfund											-0.00232	-0.00261
											(0.00161)	(0.00160)
L3.avg vcfund											-0.00189	-0.00417***
											(0.00200)	(0.00138)
N	5494	5494	5494	5280	5494	5494	5494	5280	2195	2195	82 3	787

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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