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Kill Zones? Effects of Big Tech Start-up Acquisitions on Innovation

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Kill Zones? Effects of Big Tech Start-up Acquisitions on Innovation

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ABSTRACT

This paper investigates short-term effects of big tech start-up acquisitions on innovation empirically. Innovation research has found a strong positive, causal relationship between VC investment and innovation. Using this insight, we can explore the repercussions of big tech start-up acquisitions on innovation by examining their effects on venture capital (VC) activity. We analyze a very large set of observations of more than 32,000 venture capital deals in more than 170 different segments of the tech industry and almost 400 tech start-up acquisitions made worldwide between 2010 and 2020 by Google, Facebook, Amazon, Apple, and Microsoft. Our results suggest a positive, causal impact of big tech start-up acquisitions on venture capital activity, challenging claims about the creation of “kill zones” for start-ups after acquisitions are made by the big techs. For example, after controlling for other factors that may impact VC activity, like initial public offerings (IPOs) and other mergers and acquisitions (M&As), we found an average increase of 30.7% in the total amount of VC funding towards U.S. based start-ups of the same industry segment in the four quarters following a big tech start-up acquisition. For deals targeting European start-ups, we found an increase of 32.1% in the VC funding in the first quarter after a big tech start-up acquisition. Finally, our findings show that such positive effects, when existent, persist for a few months only, and so do not seem to have lasting impacts on the innovation incentives in the the start-up ecosystem. Our empirical findings should inform current competition policy discussions on imposing restrictions to acquisitions of start-ups by the big techs.

Keywords: kill zone, platform, big tech, venture capital, innovation

JEL Codes: G11, G24, G32, G34, L41, L44

Kill Zones? Effects of Big Tech Start-up Acquisitions on Innovation

1. Introduction

For many years, Google, Amazon, Apple, Facebook, and Microsoft have actively acquired promising start-ups in their early stages of development. In the past three decades, the five U.S. big techs have collectively acquired more than eight hundred start-ups (CB Insights, 2021). Recent investigations by antitrust authorities in the United States and Europe of past big tech start-up acquisitions have intensified attention among economic scholars to the effects of big tech start-up acquisitions on innovation (U.S. Federal Trade Commission, 2020; Motta and Peitz, 2021; Varian, 2021, Katz, 2021).

There have numerous recent claims that big tech start-up acquisitions suppress entrepreneurship and stifle innovation (Schechter, 2018; Smith, 2018; McLeod, 2020; Waters, 2020). These contentions are typically based on a few interviews with venture capitalists, entrepreneurs, and activists who warn about the creation of “kill zones” for start-ups after big tech start-up acquisitions. The argument is that the presence and strategic interests of the big techs discourage further investments from venture capitalists, due to the unlikely success of a start-up that directly competes against a big and resourceful digital platform. On the other hand, a few experts counter that venture capital investment in the United States has exponentially increased in the last decade. In this perspective, big tech acquisitions have a positive impact on society by giving scale to innovative solutions that could not succeed without huge capital investments and integration with their popular platform services (Byrne, 2018; Bauer and Prado, 2020; Kennedy, 2020).

In 2020, the Antitrust Division of the U.S. Department of Justice, in partnership with Stanford University, held a Public Workshop on Venture Capital and Antitrust (U.S.

Department of Justice, 2020). During the workshop, venture capitalists, academics, and entrepreneurs discussed market characteristics and industry mechanics that may contribute to the impact of acquisitions on venture capital. Also, they discussed how venture capitalists make investment decisions in platform-dominated markets, the pros and cons of building on top of an existing platform, and how to build a successful product or service in a platform-dominated market. Finally, the workshop explored whether there is a real problem of big tech start-up acquisitions and, if so, what could be done about it.

The presented arguments suggest that the intensive start-up acquisition strategy employed by big techs may affect innovation in the short and long-run. In the short-term, these acquisitions may discourage venture capital investment in early-stage start-ups aiming at the same industry segments as the acquired ones, as venture capitalists may shy away from investing in dwarfs competing with giant digital platforms. As the innovation literature reviewed later in Section 2 strongly suggests, there is a clear positive, causal relationship between VC investment and innovation. So, a decrease in venture capital activity caused by big tech start-up acquisitions will likely be associated with a decrease in the rate of innovation. In the long-run, this intensive acquisition strategy of the big techs would make it less likely that a new, highly innovative digital platform emerges to compete against the incumbents (Prado, 2020). Absent such competition, the incentives for innovation among the current tech giants are weakened.

Although there are many claims about negative impacts of big tech start-up acquisition on innovation, very little systematic work has been done to empirically examine these concerns, the conditions under which such undesirable outcomes might materialize, and what might be done to mitigate them. In this paper we focus on investigating the alleged short-term negative effects of big tech start-up acquisitions on innovation. Our

empirical strategy, detailed in Section 3, is based on assessing the effect of big tech start-up acquisitions on venture capital activity.

For this purpose, we analyse a very large sample of data including more than 32,000 venture capital deals and almost 400 tech start-up acquisitions made worldwide between 2010 and 2020 by Google, Facebook, Amazon, Apple, and Microsoft in more than 170 different industry segments. Controlling for other factors that may impact VC activity, like IPOs and other M&As, we calculate semi-elasticities of contemporaneous and future total number of VC deals and total amount of VC funding per industry segment per quarter, with respect to a big tech start-up acquisition, by using two estimation methods. First, we employed a well-known two-way fixed effects Poisson estimation with covariates (Wooldridge, 2010).

Second, we estimated contemporaneous and future causal average treatment effects of big-tech start-up acquisitions on venture capital activity in the industry segment that received such acquisitions. Our treatments, the big tech start-up acquisitions, happened multiple times in a same industry segment and across different industry segments throughout the past years. So, for causal inference we made use of a innovative dynamic differences-in-differences setup that allows staggered treatment effects and switching treatment status, proposed by Imai, Kim, and Wang (2020).

In contrast to findings by Kamepalli et al. (2020), our results suggest a persistent, positive impact of big tech start-up acquisitions on venture capital activity. Using the two-way fixed effects estimation, we found that the total number of VC deals in an industry segment increases in average 20.17% in the four quarters following a big tech start-up acquisition. Also, using only data of deals targeting start-ups based in the United States, we found an average increase of 30.71% in the total amount of VC funding in an industry segment in the four quarters following a big tech start-up acquisition.

By using the difference-in-differences dynamic estimation setup for causal inference, we found an average increase of 4.89% in the total number of VC deals worldwide in the quarter of the acquisition in the industry segment that received the acquisition. Also, we found a 14.6% increase in the amount of VC funding driven to treated industry segments in the quarter of the treatment, an a 12.7% increase in the first quarter after the treatment. For deals targeting Europe-based start-ups, we found a causal increase of 32.1% in the level of VC funding on the treated industry segments in the first quarter after the treatment.

These results provide empirical ground supporting that acquisitions of start-ups by the big techs produce positive incentives for innovation in the short-run in the industry segments which receive such acquisitions, challenging claims about the creation of “kill zones”. However, it is important to highlight that our results do not mean that venture capital activity or innovation in the tech economy is significantly impacted by such big tech acquisitions. First, start-up specific attributes, like the quality of their management team and track-record of their founders, have a stronger impact on VC investment decisions than the market and competitive landscape of the industry segment where the start-ups play (Gompers et al., 2020). Second, we found was an increase in the total funding allocated to industry segments that received big tech start-up acquisitions. As a spillover effect, such acquisitions may result in a process of defunding adjacent industry segments, a claim that requires further research.

Our empirical findings should inform current competition policy discussions on imposing restrictions to acquisitions of start-ups by the big techs. Aligned with the findings of Cabral (2020), our work suggests that exit through acquisition is an important incentive for venture investment, and making it more difficult may end up resulting in less VC investment. Our results also do not suggest that one should foster big tech start-up

acquisitions with the goal to positively impact VC investment. Big techs' intensive acquisition strategy may have a median socially positive outcome, as they foster innovation through increased venture capital activity. However, the mean effect may be negative, as they may reduce competition by making it more unlikely that a "black swan" will emerge, a start-up that might develop into "the next big digital platform". As nowadays start-ups are very dependent on a few big techs to succeed, it is plausible to assume that more competition in platform markets should bring not only more innovation to these markets, but also reduce the risk of investing in technology start-ups in other markets. Such a risk-reduction effect should certainly have positive impacts to the entire innovation ecosystem, by fostering more start-up creation and VC investment in many segments of the technology industry.

The rest of this paper is organized as following. Section 2 reviews the literature on the effects of venture capital on innovation, and the main drivers of venture capital investment. Section 3 outlines our empirical strategy, and Section 4 provides details of the dataset used in this research. Section 5 presents our estimation methods and discusses the main empirical findings. Section 6 draws some implications of our results to competition policy and regulation of big tech start-up acquisitions. Section 7 concludes.

2. The role of venture capital investment in fostering innovation

Venture capital (VC) 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, which target firm's pre-operation, market research, product development and small-scale product launch phases (Reiff, 2020). Once a startup has established a consistent

performance record, like a growing user base, positive cash-flow, and sales growth, it may seek venture capital to expand to the next stage.

To mitigate risks, venture capitalists typically follow a staged capital infusion mechanism (Gompers & Lerner, 2001). The first round of venture capital to a firm is identified as a Series A investment. Subsequent rounds may happen and are classified as Series B, C, D and E, each new round adding capital from new or incumbent venture capitalists in exchange for equity in the firm. This stage-financing approach, along with an active role played by venture capitalists on the board of start-ups in their portfolio, have been identified in the management literature as important tools for the success of tech entrepreneurship (Da Rin et al., 2013).

2.1. Effects of venture capital on innovation

There is abundant evidence in the research literature of a close relationship between innovation and venture capital funding. The direction of this relationship, however, is contested. On the one hand, VC investors are seen as ‘company builders’ committed to provide 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 finance firms that already have a mature innovation strategy but need capital to scale, 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, that substantially increased venture capital funding in the United States, to identify a positive, causal impact of venture capital on rates of patenting. Similarly, Faria and Barbosa (2014), allowing an endogenous, dynamic relationship between VC investment and patent filings in 17

European countries observed during 2000-2009, found robust evidence supporting a positive, causal effect of venture capital activity on innovation. This effect, they conclude, would be generated mainly by later-stage VC investments.

Also, the paper by Da Rin and Penas (2007) investigates whether venture capital influences the way companies integrate new knowledge into the innovation process. For this, they analysed the absorptive capacity, or ‘the capacity of a firm to assimilate and exploit new knowledge’, of a sample of almost 8,000 Dutch firms observed from 1998 to 2004. Controlling for the selection process that compels venture capitalists to give preference to fund more innovative, promising companies, the authors found that venture capital impacted firm’s innovation strategies by directing research and development (R&D) efforts more regularly toward “make” rather than to “buy” activities.

Recently, Lerner and Ramana Nanda (2020) analysed critically the role played by VC investment in fomenting innovation. Although the authors recognize the importance of the VC investments to spur innovation, as well supported by previous literature, they discuss some limitations of this relationship. First, they argue that there is a very narrow band of technological innovations that fit the requirements of VC investors, mainly those with a short-term prospect for commercialization. However, such innovations frequently bring limited societal benefits.

Second, they claim that deep-pocket VC investors have great influence on smaller ones. This, aligned with the geographic concentration of their headquarters and a lack of diversity of their management teams, may end up creating sub-optimal incentives for innovation. For example, they argue 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 the ones with the biggest economic needs. Thirdly, the authors argue 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 for investing in the most promising companies may have created room for more “founder friendly” VC deals, which end up contributing less to raising the efficiency of innovative, early-stage start-ups.

2.2. Drivers of venture capital activity

Informational asymmetries and uncertainties frequently are associated with start-up activity. As in any risky financial activity, however, venture capitalists presumably want to make informed and rational investment decisions that maximize expected profits. Giving a plethora of start-up firms from various industry segments, venture capitalists’ constraints on making investment decisions are reportedly more related to factors like the time available to scrutinize firms and expertise in a specific industry, rather than cash availability (Gompers & Lerner, 2001; Sørensen, 2007).

VC investment decisions take into consideration a series of micro aspects of targeted start-up firms, like the quality of their management team, the industry in which they operate, the level of competition in this industry, the business model, and the product or technology offered (Gompers et al., 2020). These authors surveyed 885 institutional venture capitalists at 681 firms and concluded that the quality of the start-ups’ management team is the most important attribute driving VC investment decisions. In fact, valueing more the founders than the business-related characteristics of the start-ups is not a new trend guiding venture investment. In the late 1990s, Feeney et al., (1999) interviewed around 150 venture capital investors to understand their investment decision-making process. The authors found that venture capitalists value ‘owner’ attributes, like management track-record, integrity, and commitment, more than ‘business’ prospects, like risk-adjusted potential returns.

Another important aspect identified by both Feeney et al., (1999) and Gompers et al. (2020) is having a feasible exit path for the venture investment, either via an Initial Public Offering (IPO) or through Merger and Acquisitions (M&As). The most recent study explains that exits represent the main opportunity for VC investors to return capital to their investors and secure their profit share. Also, a track-record of successful exits is important for venture capitalists to establish a reputation and attract new investors (Gompers, 1996). Past and recent research suggests that geographic proximity plays an important role driving VC's investment decisions, since such deals frequently involve post-entry active monitoring and board service (Lerner, 1995; Lerner and Nanda, 2020).

More recently, in U.S. Department of Justice (2020), Ram Shriram, an experienced VC investor and Google Board member, explained that:

“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. Of course, market spaces matter, but what matters most is the team, the quality of the team that you're investing in, and whether the ideal, or what they have to present, has any kind of defensibility from a technology perspective. And beyond that, it's a question of how capital efficient the idea is, and where it can go, and how broad and how big the market is for what they're going after.”

His views were echoed by other VC investors in the same workshop. However, some new criteria were added to the VC decision-making process. Kelland Reilly, another experienced VC investor, highlighted that start-up investment decisions consider the scale and the density of the data owned by the start-up, and how the data is key for its business model. Also, it was pointed out that start-ups that collect data and create feedback loops, where consumers provide data, that improve the service, that attract more consumers, should attract more funding, illustrating the importance of data-driven business models to venture capitalists nowadays.

In the same event, other VC investors shed light on investing in tech markets where platforms are omnipresent. It was said that most start-ups are really dependent on services provided by the big techs, like cloud services, map services, etc. Moreover, it was mentioned that the more dependent a start-up is on a big tech firm, the worse the start-up is viewed by VC investors, as this dependence may represent a risky single point of failure.

In order to mitigate search costs and time, as well as the risks associated with venture investing, VCs frequently syndicate with other VCs (Hochberg et al. 2007, Lerner and Nanda, 2020). In fact, there is empirical evidence showing that, in order to limit the risk that bad deals get funded, even experienced venture capitalists value a “second opinion” of other VCs with similar level of expertise (Lerner, 1994). Consistent with previous studies, Gompers et al. (2020) found that VC firms syndicate in 65% of their investments, in average, and the main reasons for doing so are capital constraints, complementary expertise, and risk sharing.

3. Empirical strategy

As reviewed in Section 2, the investment decision of a typical venture capitalist considers a number of factors. First, start-ups’ own characteristics, as the maturity of its management team and potential of its business model. Second, the level of expertise of the venture capitalist with the industry segment where the start-up plays. Third, market conditions of the industry segment that will drive the potential of the start-up to scale and lead to a successful exit strategy for the venture investment, usually through an IPO or an acquisition, most likely by the incumbent firm of the industry segment.

Acquisitions of start-ups by Google, Facebook, Amazon, Apple, and Microsoft may affect the likelihood of venture capitalists to invest in a start-up in the same industry segment for several reasons. First, these digital platforms have access to superior amounts

of data on consumer markets compared to most of the venture capitalists. 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 may attract venture capitalists to invest in start-ups of the same industry segment picked by the big tech. Second, having a resourceful, large-scale digital platform playing in an industry segment should attract venture investment in start-ups focused on complementary innovations (Foerderer et al., 2018). Third, a big tech start-up acquisition may increase expectations that additional start-ups will be acquired in the near future by the big tech. 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 increased competition after the entry of a big tech in a new industry segment through an acquisition may discourage venture investment in other start-ups in the same industry segment. As start-ups are very dependent on a few big techs to host their technological solutions, distribute their apps to end users, advertise their products to reach new customers, etc., the risk of investing in a start-up should strongly increase after a big tech acquisition in the same industry segment. Moreover, the increased risk of neighboring start-ups having their products copied by a competing big tech should also repeal venture investment.

In fact, big tech start-up acquisitions may impact venture capital activity in different ways, when compared to start-up acquisitions made by other big corporations. However, little robust empirical research has been conducted to unveil the net effect of big tech start-up acquisitions on venture capital activity. In the unique empirical work that we have seen so far, Kamepalli et al. (2020) argues that the unlikely success of small start-ups directly competing against a big and resourceful digital platform creates “kill zones” for start-ups, who may face considerable struggles to obtain VC funding after a big tech

acquisition in their industry segment. However, the authors analyzed the effect of only nine out of hundreds of start-up acquisitions made by the big techs in the last twenty years. Moreover, their empirical strategy does not include important control variables, as the big techs are neither the unique nor the biggest start-up acquirers that may influence venture capital (U.S. Department of Justice, 2020).

Our empirical analysis seeks to overcome these issues by relying on a very large sample of data including more than 32,000 venture capital deals, more than 400 big tech start-up acquisitions, as well as thousands of Initial Public Offerings (IPOs) and mergers and acquisitions (M&As) that happened from 2010 to 2020 in more than 170 different industry segments. 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.

3.1. Semi-elasticities of VC activity with respect to big tech start-up acquisitions

Let us consider that an industry segment $i \in I$ receives in each period of time $t \in T$ a total amount of venture-capital funding ($vcfund_{i,t}$), through a number of venture-capital deals ($vcdeals_{i,t}$), to support the creation and delivery of innovative products and services. The venture capital investment to support innovation may be affected by present or past big tech start-up acquisitions in each industry segment. To model such big tech start-up acquisitions, 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 will be detailed in Section 4, 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 impact venture investment, namely the total number of IPOs ($ipo_{i,t}$), and M&As of VC-backed start-ups

($ma_{i,t}$). Controlling for other exit events that may impact venture capital activity is important to differentiate the effect of big tech start-up acquisitions from general exit events, as the interest of a digital platform in an industry segment may have special impact on the risk assessment performed by venture capitalist before investing in a start-up, as discussed in Section **Error! Reference source not found.**. Also, 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 their start-ups to receive venture investment.¹

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, like the presence of low sunk costs and high economies of scope and scale that may raise expected payoffs in certain technology-intensive industry segments, so attracting 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, like the COVID-19 pandemic.

Finally, it is important to notice that we foresee a very dynamic relationship between the big tech start-up acquisitions and the venture capital activity. In fact, 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 future, as venture capitalists internalize the new market conditions of the industry segment. So, we include in the model three lagged terms of the explanatory variables for capturing these longer-run

¹ 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 level, what may attract more VC investment. Gompers et al. (2020) found that past IPOs are an important sign for VC investors regarding the feasibility of an exit path through an IPO for their investment in a start-up.

effects. Equations (1) and (2) present the dynamic equations that we are interested in estimating. The exponential functional form was chosen due to the fact that both $vcdeals_{i,t}$ and $vcfund_{i,t}$ receive only zero or strictly positive values. This choice is further discussed in Section 5 after we detail the dataset used in the econometric estimation.

$$Y_{i,t}^v = c_i \varepsilon_{i,t} \exp(\alpha^v + \beta_0^v plat_{i,t} + \beta_1^v plat_{i,t-1} + \beta_2^v plat_{i,t-2} + \beta_3^v plat_{i,t-3} + \mathbf{X}_{i,t} \gamma_0^v + \mathbf{X}_{i,t-1} \gamma_1^v + \mathbf{X}_{i,t-2} \gamma_2^v + \mathbf{X}_{i,t-3} \gamma_3^v + \lambda_t) \quad (1)$$

In equation (1), the dependent variable $Y_{i,t}^v$ may be either $vcdeals_{i,t}$ or $vcfund_{i,t}$, with the superscript $v = \{vcd, vcf\}$ indicating each, respectively. The constants α and ω are cross-sectional and time-invariant means of the dependent variable, while $\varepsilon_{i,t}$ and $u_{i,t}$ are specification error terms. Furthermore, $\mathbf{X}_{i,t-k} \gamma_k^v = \gamma_{1,k}^v ipo_{i,t-k} + \gamma_{2,k}^v ma_{i,t-k}$, for any $k = \{0, 1, 2, 3\}$. The coefficients of interest are β_0^v , β_1^v , β_2^v , and β_3^v , the semi-elasticities of $Y_{i,t}^v$ 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.

3.2. Causal average treatment effects of big-tech start-up acquisitions on venture capital activity

In order to investigate causal effects of big-tech start-up acquisitions on $vcdeals_{i,t}$ and $vcfund_{i,t}$, 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 in the same industry segment along the years (as detailed in Section 4

below), and will likely have short-term effects (e.g., 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 years.

Given 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 caused by big tech start-up acquisitions on venture capital activity. One alternative would be to investigate only the effects on industry segments who received treatment for the first time. This would substantively impact the efficiency of our estimation and the robustness of our results, as most of the big tech start-up acquisitions happen in industry segments that already received treatment in the past. Therefore, in order to identify causal average effects of big tech start-up acquisitions on $vcdeals_{i,t}$ and $vcfund_{i,t}$, we utilize the empirical strategy proposed by Imai, Kim, and Wang (2020), which uses matching methods to identify causal inference in panel datasets with switching treatment status. Further details of the estimation methods are provided in Section 5.2.

For now, assume $treat_{i,t}$ 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 causal effects that we want to identify can be defined by equation (2).²

$$\delta^v(F, L) = \mathbb{E}\{Y_{i,t+F}^v \left(\text{treat}_{i,t} = 1, \text{treat}_{i,t-1} = 0, \{\text{treat}_{i,t-l}\}_{l=2}^L \right) - Y_{i,t+F}^v \left(\text{treat}_{i,t} = 0, \text{treat}_{i,t-1} = 0, \{\text{treat}_{i,t-l}\}_{l=2}^L \right) \mid \text{treat}_{i,t} = 1, \text{treat}_{i,t-1} = 0\} \quad (2)$$

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 two time periods 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.

4. Data

Our empirical analysis relies on data of venture capital deals, big tech start-up acquisitions, IPOs, and mergers and acquisitions (M&As) of VC-backed firms consummated from January 1st, 2010 to December 31st, 2020. This information was retrieved from the database gathered by CB Insights³. This source classifies each start-up as belonging to 20 economic sectors, and hundreds of industries, and subindustries. The dataset contains information on a variety of features of each deal, like the name of the start-up that received the VC funding, its location (continent, country, state and city), amount funded in the deal, the investment round (Series A to E), day, month and year when each deal was closed, among others. Due to use conditions imposed by CB Insights,

² Details on the selection of L and F are provided in Section 5.2.

³ The data was retrieved from the CB Insights business intelligence platform, available at <https://www.cbinsights.com/>, using a license provided for Michigan State University for research purposes.

the dataset to which we had access only includes information of the main two tech-related economic sectors: Internet, and Mobile Telecommunications.

These two economic sectors alone comprehend approximately 54% of the total 80,695 VC deals reported by CB Insights in the 2010-2020 period. More importantly, they account for 404, or approximately 70% of the total 582 big tech start-up acquisitions that happened in the same period. Among the industries which comprise these two economic sectors, the big tech start-up acquisitions were heavily concentrated on four of them: Internet Software & Services, eCommerce, Mobile Commerce, and Mobile Software & Services. In fact, 392 out of the 404 big tech start-up acquisitions happened only in these four industries. Also, 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.

However, given the aim of identifying the effects of big tech start-up acquisitions on VC investment provided to other similar start-ups, we narrowed down the analysis and focused on identifying the effects on the subindustry level under this four industries. With this approach, the 32,367 VC deals and 392 big tech start-up acquisitions were grouped in 173 unique sector-industry-subindustry triads, hereafter simply referred as industry segments. Table B in the annex provides further details for each industry segment. Information on the number of IPOs and M&As of VC-backed companies for each industry segment was also retrieved from the CB Insights database. 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.

Table 1 presents the geographic distributions of deals, and Table 2 provides summary statistics of these variables for deals that involving start-ups worldwide, deals

only involving U.S.-based start-ups, and deals involving only Europe-based start-ups. The development of these variables over all industry segments per quarter are presented in Figures 1, 2, and 3 for each of the three geographic breakdowns. Finally, Figures 4, 5, and 6 show the distribution of treatment (big tech start-up acquisitions, represented by the variable $treat_{i,t}$, already detailed in Section 3.2) worldwide, in the United States, and in Europe, respectively.

Table 1- Geographic distribution of the variables from 2010 to 2020 in tech-related industries

Panel:	All			U.S.			Europe		
Ind. segments:	All	Treat	Untreat	All	Treat	Untreat	All	Treat	Untreat
<i>Variables</i>									
<i>VC deals</i>	32367	23726	8641	17238	12662	4576	5342	3676	1666
<i>VC funding</i>	749.3	464.6	284.7	335.4	213.4	122.0	72.4	51.7	20.7
<i>Plat. acqui.</i>	392	392	0	292	292	0	66	66	0
<i>IPOs</i>	1447	1074	373	446	311	135	260	162	98
<i>M&As</i>	6149	4971	1178	3951	3161	790	1118	714	404

Industry segments that received treatment are those that had at least one big tech start-up acquisition between 2010 and 2020.

VC Funding is reported in billions of dollars.

Table 2.1- Descriptive Statistics – Worldwide

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>VC deals</i>	7612	4.252	7.823	0	68
<i>VC funding</i>	7612	98.44	336.071	0	14386.99
<i>Plat. acqui.</i>	7612	.051	.251	0	5
<i>IPOs</i>	7612	.19	.601	0	7
<i>M&As</i>	7612	.808	1.717	0	19
Treated industry segments					
<i>VC deals</i>	3608	6.576	9.358	0	68
<i>VC funding</i>	3608	128.777	363.326	0	14386.99
<i>Plat. acqui.</i>	3608	.109	.355	0	5
<i>IPOs</i>	3608	.298	.735	0	7
<i>M&As</i>	3608	1.378	2.19	0	19
Untreated industry segments					
<i>VC deals</i>	4004	2.158	5.31	0	68
<i>VC funding</i>	4004	71.104	306.95	0	7373.39
<i>Plat. acqui.</i>	4004	0	0	0	0
<i>IPOs</i>	4004	.093	.423	0	7
<i>M&As</i>	4004	.294	.853	0	11

VC Funding is reported in millions of dollars.

Table 2.2 - Descriptive Statistics – U.S. Panel

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>VC deals</i>	7612	2.265	4.468	0	44
<i>VC funding</i>	7612	44.06	130.688	0	4100
<i>Plat. acqui.</i>	7612	.038	.215	0	4
<i>IPOs</i>	7612	.059	.278	0	4
<i>M&As</i>	7612	.519	1.232	0	13
<i>Treated industry segments</i>					
<i>VC deals</i>	3300	3.837	5.8	0	44
<i>VC funding</i>	3300	64.662	133.75	0	1591.22
<i>Plat. acqui.</i>	3300	.088	.319	0	4
<i>IPOs</i>	3300	.094	.348	0	4
<i>M&As</i>	3300	.958	1.653	0	13
<i>Untreated industry segments</i>					
<i>VC deals</i>	4312	1.061	2.484	0	34
<i>VC funding</i>	4312	28.293	126.057	0	4100
<i>Plat. acqui.</i>	4312	0	0	0	0
<i>IPOs</i>	4312	.031	.205	0	4
<i>M&As</i>	4312	.183	.573	0	7

VC Funding is reported in millions of dollars.

Table 2.3 - Descriptive Statistics – Europe Panel

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>VC deals</i>	7612	.702	1.674	0	21
<i>VC funding</i>	7612	9.517	36.42	0	616.72
<i>Plat. acqui.</i>	7612	.009	.093	0	1
<i>IPOs</i>	7612	.034	.205	0	5
<i>M&As</i>	7612	.147	.478	0	9
<i>Treated industry segments</i>					
<i>VC deals</i>	1760	.947	1.663	0	17
<i>VC funding</i>	1760	11.759	36.167	0	555.5
<i>Plat. acqui.</i>	1760	.037	.19	0	1
<i>IPOs</i>	1760	.056	.257	0	3
<i>M&As</i>	1760	.23	.536	0	4
<i>Untreated industry segments</i>					
<i>VC deals</i>	5852	.628	1.671	0	21
<i>VC funding</i>	5852	8.843	36.472	0	616.72
<i>Plat. acqui.</i>	5852	0	0	0	0
<i>IPOs</i>	5852	.028	.186	0	5
<i>M&As</i>	5852	.122	.456	0	9

VC Funding is reported in millions of dollars.

Figure 1 – Distribution of variables per quarter for worldwide deals

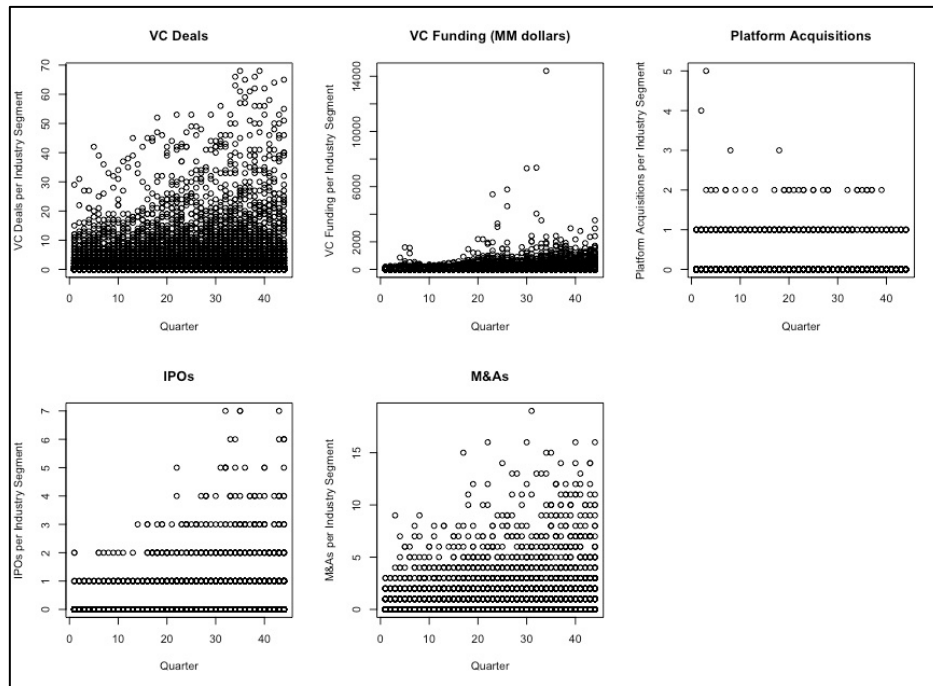


Figure 2 - Distribution of variables per quarter for U.S. deals

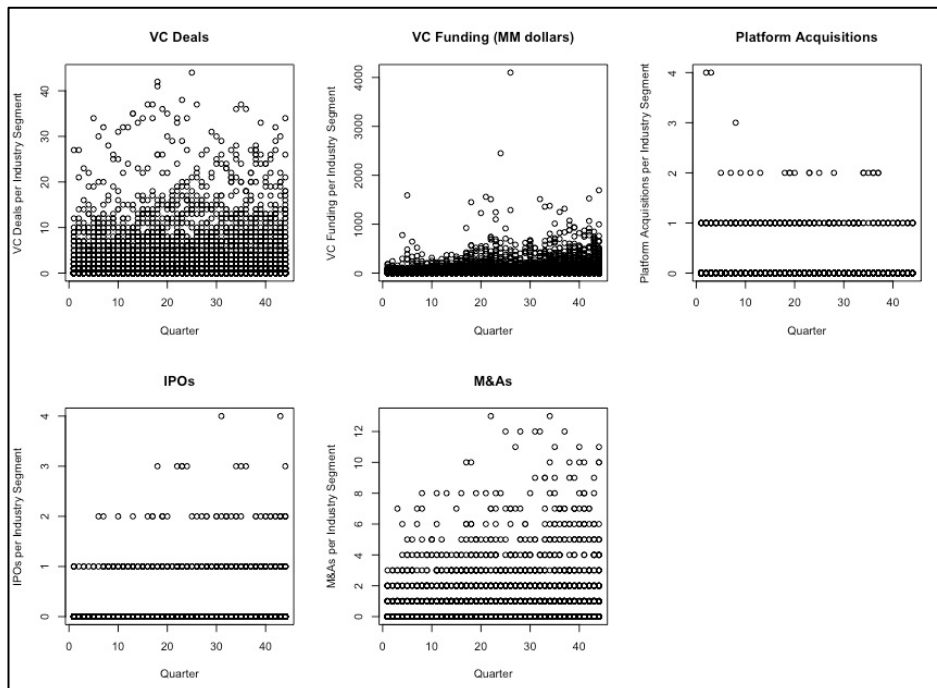


Figure 3 – Distribution of variables per quarter for Europe deals

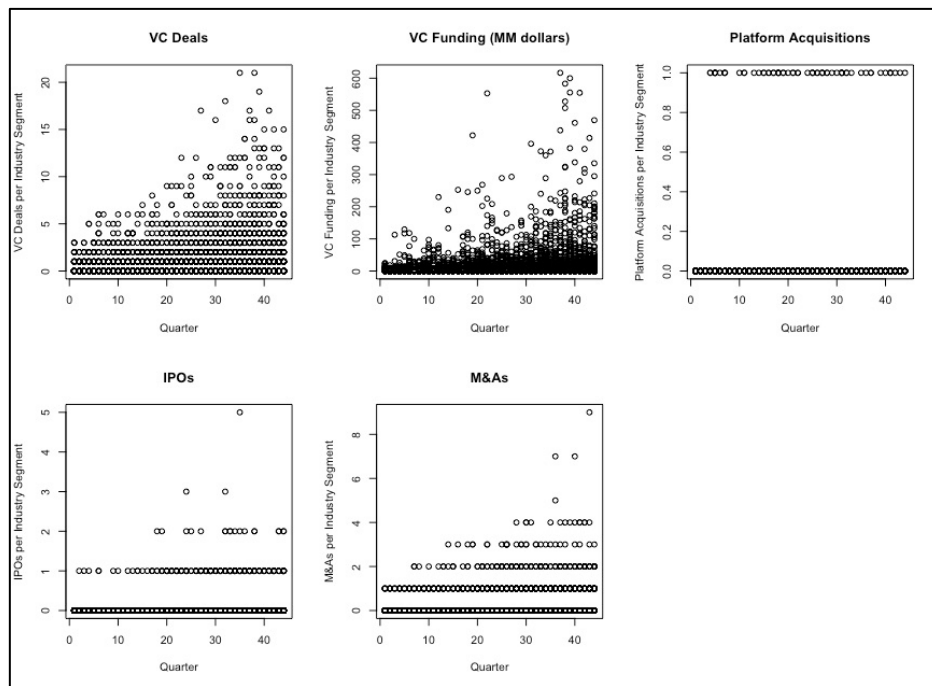


Figure 4 – Distribution of treatment through industry segments and quarters worldwide

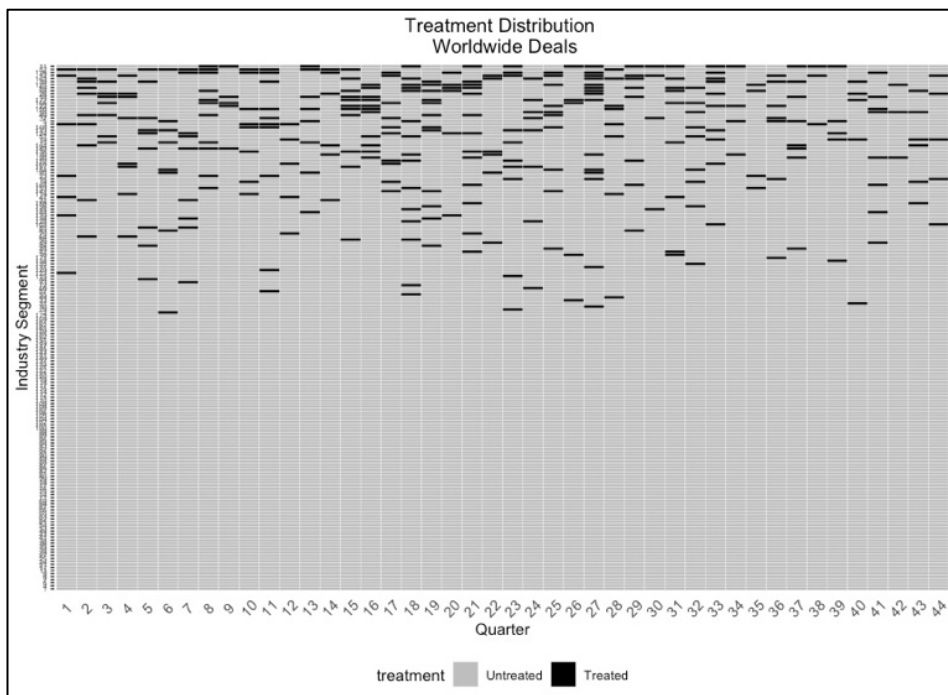


Figure 5 – Distribution of treatment through industry segments and quarters in the United States

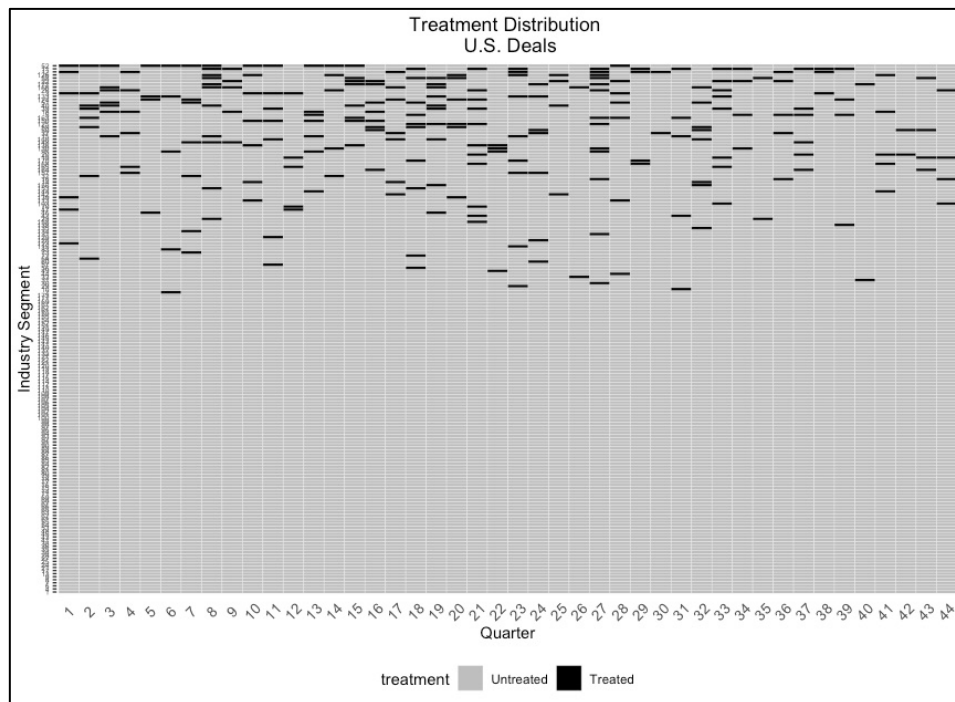
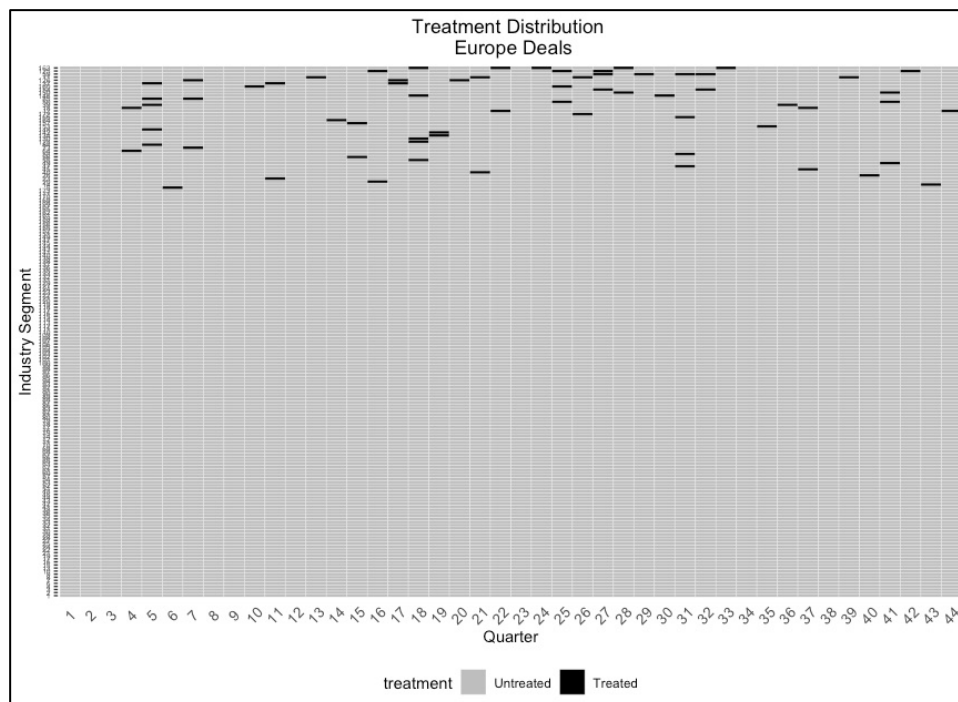


Figure 6 – Distribution of treatment through industry segments and quarters in Europe



5. Estimation methods and main results

5.1. Semi-elasticities of VC activity with respect to big tech start-up acquisitions

Table 3 shows results of the two-way fixed effects estimation of the dynamic model specified by equation (1), using the entire sample of VC capital deals worldwide from 2010 to 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. 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 equation (1) but without including the controlling variables $ipo_{i,t-k}$ and $ma_{i,t-k}$, for $k = \{0,1,2,3\}$, while columns 2 and 5 present estimates with the inclusion of such controlling variables.

Considering that the dependent variables are non-negative, hence an exponential estimation model is specified by equation (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 to always have positive predicted results. Also, we do not need to deal with log transformations like $\log(1+y)$, 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 effect of platform acquisitions on 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.

An attractive feature of the Poisson estimator is that it allows the assumed Poisson distribution of the dependent variable to be arbitrarily misspecified, and any kind of serial correlation can also be present (Wooldridge, 2010). However, considering that the panel

dataset includes information from 44 time-periods (quarters) and 173 industry segments⁴, columns 3 and 6 present estimates obtained after addressing serial correlation by including multiple lags of the dependent variables among the regressors⁵. Furthermore, as an additional robustness check, we included in 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 testing 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 A1 in the annex, showed no statistically significant effects of current shocks in the level of VC deals and funding on future levels of platform acquisitions per industry segment per quarter.

Table 3 – Results of the two-way fixed effects Poisson estimation – Worldwide VC activity

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:	VC Deals	VC Deals	VC Deals	VC Funding	VC Funding	VC Funding
Indep. Variables						
<i>plat</i>	0.0298 (0.0317)	0.0183 (0.0318)	0.0229 (0.0279)	0.0279 (0.0762)	0.0187 (0.0759)	0.0197 (0.0751)
<i>plat (1 lag)</i>	0.0627 (0.0411)	0.0509 (0.0397)	0.0474* (0.0259)	0.0734 (0.0725)	0.0698 (0.0792)	0.0712 (0.0781)
<i>plat (2 lags)</i>	0.0812** (0.0346)	0.0711** (0.0338)	0.0704*** (0.0197)	0.195* (0.113)	0.198* (0.110)	0.198* (0.110)
<i>plat (3 lags)</i>	0.0668** (0.0309)	0.0616* (0.0323)	0.0610*** (0.0207)	0.148* (0.0844)	0.119 (0.0839)	0.117 (0.0829)
Combined effects						
<i>plat</i>	0.2405* (0.1255)	0.2019* (0.1217)	0.2017*** (0.006)	0.4444 (0.2729)	0.4049 (0.2638)	0.4057 (0.2604)
Obs	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) include also t-1 to t-4 lagged dependent variables for correcting for serial correlation, while the estimation model reported in column (6) include also 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

⁴ Serial correlation is not consider a big issue by the modern econometric literature in a scenario of small T and large N. However, as T in our dataset is relatively large (44 quarters), we opted to deal with serial correlation explicitly in the model specification. However, results showed in columns 3 and 6 are not significantly different than the ones of columns 2 and 5, as the Poisson regressor is robust under serial correlation.

⁵ Four lagged dependent variables were included in the model of column 3, while just one in the model of column 6, as any additional lagged terms of the dependent variables were found non statistically significant.

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, while 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 A1 in the annex.

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%].⁶ These results support the 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. 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 Europe-based VC deals, platform acquisitions, IPOs, and M&As of VC-backed start-ups, respectively. Standard errors of the estimates reported were also clustered on the industry segment level, and are robust to heteroskedasticity.

⁶ The combined estimate is calculated through the linear combination of the four estimates found for the variables $plat_{i,t-k}$, for $k = \{0,1,2,3\}$.

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, as well as complete results with estimates of all controlling variables are reported in Tables A2 and A3 in the annex.

Table 4 – Results of the two-way fixed effects Poisson estimation – U.S. VC activity

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:	VC Deals	VC Deals	VC Deals	VC Funding	VC Funding	VC Funding
Indep. Variables						
<i>plat</i>	0.0205 (0.0340)	0.00550 (0.0325)	0.0161 (0.0263)	0.0823 (0.0677)	0.0492 (0.0634)	0.0317 (0.0604)
<i>plat (1 lag)</i>	0.0971** (0.0398)	0.0789** (0.0360)	0.0786*** (0.0245)	0.0999*** (0.0346)	0.0782** (0.0347)	0.110** (0.0474)
<i>plat (2 lags)</i>	0.125*** (0.0351)	0.104*** (0.0345)	0.0847*** (0.0262)	0.306*** (0.111)	0.283*** (0.106)	0.147** (0.0608)
<i>plat (3 lags)</i>	0.0606 (0.0410)	0.0506 (0.0398)	0.0310 (0.0307)	0.195* (0.102)	0.160 (0.0984)	0.0179 (0.0564)
Combined effects						
<i>plat</i>	0.3031** (0.1314)	0.2385** (0.1205)	0.2105*** (0.0701)	0.6835** (0.2660)	0.5701** (0.2339)	0.3071** (0.1435)
Obs	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) include also 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 – European VC activity

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

Estimation models reported in columns (3) and (6) include also t-1 to t-3 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

Regarding the effects of big tech acquisitions of U.S.-based start-ups, the results 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. They 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 happened in a given industry segment. Furthermore, an increase of 11%, and 14.7% in the total amount of VC funding were found in the same period.

The results suggest a positive increase of 21.05% and 30.71% on the total number of VC deals and on the total amount of VC funding, respectively, from the quarter of the acquisition until the third quarter after the acquisition, with 95% confidence interval of

[7.31%, 34.79%] and [2.58%, 58.84%], respectively. Although these confidence intervals are pretty wide, they provide empirical ground for the claim that acquisitions of U.S.-based start-ups by the big techs produce positive incentives on innovation in the industry segments of the U.S. tech ecosystem which receive such acquisitions. As 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, as vast empirical literature predict 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, displacing claims that associate big tech acquisitions with discouragement for VC investment in other European start-ups playing in the same industry segment. An increase of 11%, and 31% in the total number of VC deals were also 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 a strong positive, statistically significant average increase 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%].

5.2. Causal average treatment effects of big tech start-up acquisitions on venture capital activity

For estimating the average causal treatment effects of big tech start-up acquisitions on venture capital activity, $\delta^v(F, L)$, specified in equation (2) of Section 3.2, we rely on the

estimation procedure proposed by Imai, Kim, and Wang (2020). In summary, for each treated observation, we find a set of control observations with the same treatment history up a certain number (L) of time periods before the treatment. After finding a matched set for each treated observation, we use a propensity score weighting (PSW) procedure to estimate a counterfactual outcome for each treated unit, based on the weighted average of the outcomes of the units included in each matched set. Then, we apply the difference-in-differences estimator using only the treated observations and their respective, refined matched set of control observations.

5.2.1. 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 scenario, this means assuming that a big tech start-up acquisition in a industry segment should not impact 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 availability of capital, we believe it is reasonable to maintain this assumption for the purposes of this paper, with the goal to conduct additional analysis in the future.

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 2.2), which suggests a short-term effect of big tech start-up acquisitions on VC activity. The third assumption is that parallel trends exist between treated and matched control observations after conditioning on the treatment, covariates, and outcome variable

histories (up to L time periods). Equation (3) formalizes such parallel trends assumption, which is maintained by adopting the matching procedure with weighting proposed by Imai, Kim, and Wang (2020), as detailed in the next subsection.

$$\begin{aligned} & \mathbb{E} \left[Y_{i,t+F}^v \left(\text{treat}_{i,t} = 0, \text{treat}_{i,t-1} = 0, \{\text{treat}_{i,t-l}\}_{l=2}^L \right) - Y_{i,t-1}^v \mid \text{treat}_{i,t} = 1, \text{treat}_{i,t-1} = 0, \{\text{treat}_{i,t-l}, Y_{i,t-1}^v\}_{l=2}^L, \{\text{ipo}_{i,t-l}\}_{l=0}^L, \{\text{ma}_{i,t-1}\}_{l=0}^L \right] \\ & = \mathbb{E} \left[Y_{i,t+F}^v \left(\text{treat}_{i,t} = 0, \text{treat}_{i,t-1} = 0, \{\text{treat}_{i,t-l}\}_{l=2}^L \right) - Y_{i,t-1}^v \mid \text{treat}_{i,t} = 0, \text{treat}_{i,t-1} = 0, \{\text{treat}_{i,t-l}, Y_{i,t-1}^v\}_{l=2}^L, \{\text{ipo}_{i,t-l}\}_{l=0}^L, \{\text{ma}_{i,t-1}\}_{l=0}^L \right] \quad (3) \end{aligned}$$

5.2.2. Matching procedure

The first step of the matching procedure was selecting 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). While a large L makes this assumption less restrictive, it may reduce the chances of finding, in the matching procedure, controlling industry segments with the same history of treatment than the treated industry segments, potentially yielding less precise estimates. In order to avoid having to discard too many treated observations in the estimation, we chose $L=2$, although different windows were tested ($L=3$ and $L=4$) and similar results found.

Once L is defined, we matched treated observations with untreated observations of the same time period that had the same treatment history in $t-1$ and $t-2$. This allowed us to build a matched set of control observations for each treated observation. Figure 7 illustrates the matching procedure. Each treatment observation has a set of same-time control matched observations 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 of $t=5$, as none of the control observations have the same treatment history.

Figure 7 – Illustration of the matching procedure for $L=2$

		Time					
		t=1	t=2	t=3	t=4	t=5	t=6
Units	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

5.2.3. Weighting of matched control observations

As proposed by Imai, Kim, and Wang (2020), once the matched sets for each treatment observation was found, we estimated the ATT of big tech start-up acquisitions on the total number of VC deals per industry segment per quarter, $\widehat{\delta^{vcd}}(F, L)$, and on the total amount of VC funding per industry segment per quarter, $\widehat{\delta^{vcf}}(F, L)$. For each treated observation of industry segment i and quarter t , we estimated the counterfactual outcome

$$\widehat{Y_{i,t+F}^v} \left(treat_{i,t} = 0, treat_{i,t-1} = 0, \{treat_{i,t-l}\}_{l=2}^L \right)$$

by calculating the weighted average outcome of the control observations in each matched set.

We used the well-known inverse propensity score weighting (PSW) method proposed by Hirano, Imbens and Ridder (2003). Essentially, we calculated a weight for each control observation included in a matched data set, based on its propensity score. A greater weight was assigned to control observations with a more similar history of covariates

$$\left(\{ipo_{i,t-l}\}_{l=0}^L, \{ma_{i,t-l}\}_{l=0}^L \right) \text{ and outcome values } \left(\{Y_{i,t-l}^v\}_{l=2}^L \right), \text{ compared to the treated}$$

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, essential for identification of average causal treatment effects. Other weighting methods, like the propensity score matching (PSM) procedure, were also tested, yielding similar results, but with more restrictive assumptions than the PSW method reported, 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). 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, yielding the propensity scores for each treatment and matched control observation. The level of similarity between the treatment and control observations was then assessed based on the differences of their calculated propensity scores.

5.2.4. Causal average effects of big tech start-up acquisitions

Once we 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 difference-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. These procedure yields the causal average treatment effects (ATT) estimates for the quarter of the treatment, as well as for two leading quarters ($F=2$). Detailed results for each estimate are provided in Table 6 for deals consummated worldwide, in the U.S., and in Europe. Figure 8 provides a graphical illustration of the estimates, along with their 90% confidence intervals. The choice of F was made to guard coherence with the assumed carry over effect of two time-periods ($L=2$) detailed in Section 5.2.2. Choosing a larger F would complicate the interpretation of the estimated ATTs, as it would increase the chances of treated industry segments receiving another treatment during the F lead time periods.

Table 6 – Results of causal inference

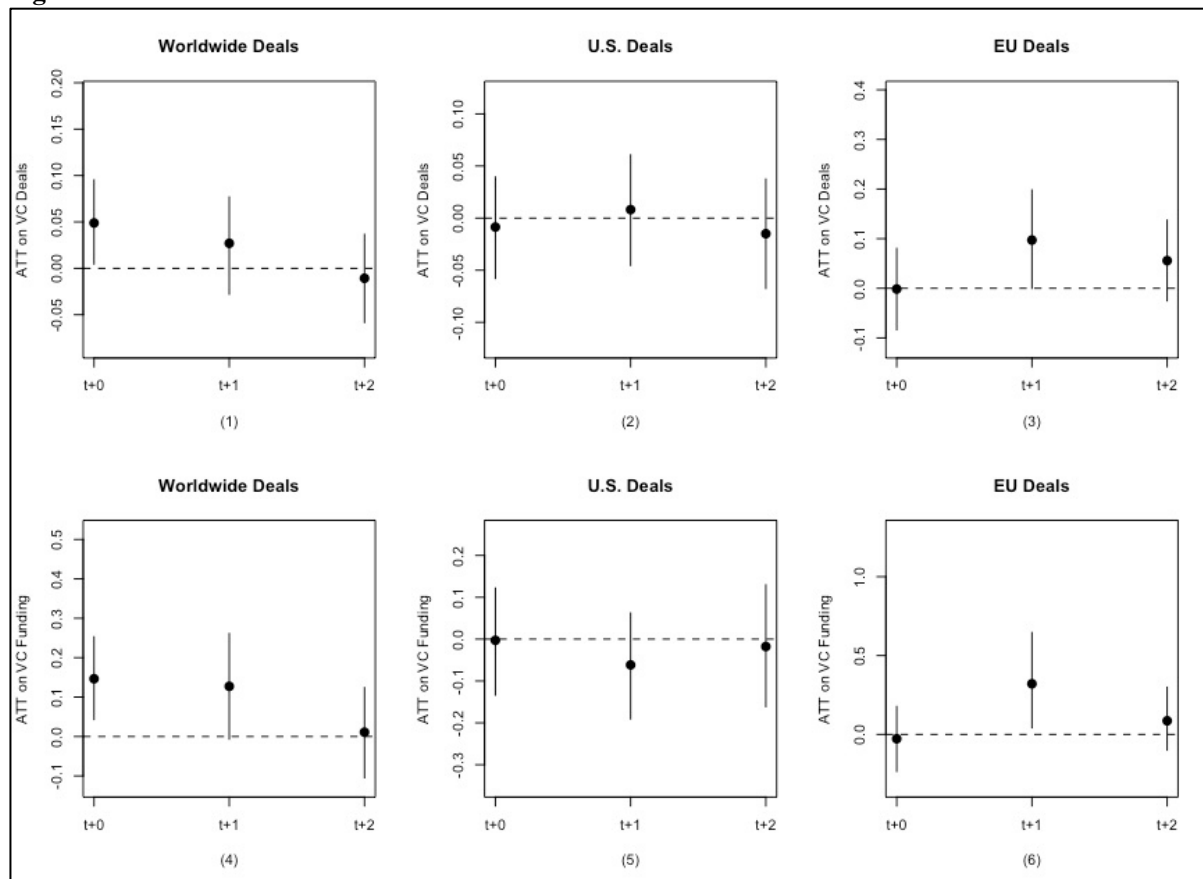
	(1)	(2)	(3)	(4)	(5)	(6)
Panel:	Worldwide	U.S.	Europe	Worldwide	U.S.	Europe
Dep. Variable:	VC Deals	VC Deals	VC Deals	VC Fund	VC Fund	VC Fund
<i>ATT</i>	0.0489*	-0.0086	-0.0015	0.1465**	-0.0028	-0.0275
	(0.0285)	(0.0306)	(0.0513)	(0.061)	(0.0772)	(0.1245)
<i>ATT 1 quarter post</i>	0.027	0.0081	0.0972	0.1274*	-0.0616	0.3209*
	(0.033)	(0.0347)	(0.0624)	(0.0764)	(0.0817)	(0.1757)
<i>ATT 2 quarters post</i>	-0.0107	-0.015	0.0557	0.0109	-0.0177	0.0863
	(0.0302)	(0.0344)	(0.0477)	(0.0706)	(0.0907)	(0.123)
Treated Obs.	262	204	63	262	204	63
Avg. Untreated Obs.	127.6	138	154.4	127.6	138	154.4

Outcome variables were log transformed.

Average untreated observations included in the matched control set of each treated observation.

Standard errors in parentheses were calculated through a block-bootstrapped procedure, with 1000 iterations. For details, see Imai, Kim, and Wang (2020, p.20).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 8 – Estimated causal effects of treated over time

90% confidence intervals based on block-bootstrapped standard errors using 1,000 iterations. For details, see Imai, Kim, and Wang (2020, p.20).

Using data of deals consummated worldwide, the results presented in graphs (1) and (4) of Figure 8 suggest small, but statistically significant positive causal effects of big tech start-up acquisitions on the total number of VC deals and amount of VC funding in treated industry segment in the quarter of the acquisition. An average increase of 4.89% on the total number of VC deals was found in the quarter of the treatment, with a 90% confidence interval of [0.5% , 9.5%]. The effects on the first and second quarter after the treatment were not statistically different than zero. Regarding the amount of VC funding driven to treated industry segments, we found a 14.6% increase in the quarter of the treatment, an a 12.7% increase in the first quarter after the treatment. These results are consistent with the ones reported in columns (3) and (6) of Table 3, 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.

Analysing the effect big tech start-up acquisitions consummated in the United States on venture capital activity in the United States, no statistically significant causal effect was found, as reported by graphs (2) and (4) of Figure 8. One possible explanation for these results may be the existence of a highly dynamic venture capital activity in the United States. There, VC investors may have more information about promising industries and start-ups, and more options to decide about the allocation of venture funding without relying too much on trends set by big tech start-up acquisitions.

Contrarily, we have found positive, statistically significant causal effects of big tech start-up acquisitions on VC activity in Europe. By using only acquisitions of start-ups based in Europe by the big techs, we found a 32.1% average increase in the level of VC funding on the treated industry segments in the first quarter after the treatment, with a wide 90% confidence interval of [3.5% , 60.7%]. These results are also aligned with the results of the two-way fixed effects Poisson estimation, reported in Table 5. They challenge claims that big tech start-up acquisitions discourage VC investment in other European start-ups .

Summing-up, our empirical analysis, based on thousands of venture capital deals, M&As, IPOs, and big tech start-up acquisitions consummated from 2010 to 2020 in more than 170 industry segments of the tech-related economy, provide robust ground for rejecting the existence of measurable negative effects of big tech start-up acquisitions on VC activity in these industry segments. Instead, causal, statistically significant positive effects were found, except for the highly dynamic U.S. venture capital ecosystem. Also, our findings show that such positive effects, when existent, persist for a few months only,

and so do not seem to have lasting impacts on the innovation incentives in the the start-up ecosystem.

6. Implications for Competition Policy and Regulation

Our empirical investigation of the effects of big tech start-up acquisitions shows strong evidence of a positive, statistically significant increase in venture investment in the industry segments where the acquired start-ups play. These results challenge claims about the existence of short-term, negative impacts of these acquisition on innovation due to the creation of “kill zones” for start-ups. This finding should inform current competition policy discussions on imposing restrictions on acquisitions of start-ups by the big techs. Aligned with the findings of Cabral (2020), our empirical results suggests that exit through acquisition is an important incentive for venture investment, and making it more difficult may end up resulting in less VC investment.

On the other hand, our results do not suggest that one should foster big tech start-up acquisitions. Although big techs’ intensive acquisition strategy may have a median socially positive outcome, as they foster innovation through increased venture capital activity, the mean effect may not be positive, as acquisitions may eliminate a “black swan” competitor, a start-up that could be “the next big digital platform”. As start-ups are very dependent on a few big techs to succeed, it is plausible to assume that more competition in platform markets like social media, App stores, cloud services, etc., should bring not only 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 positive impacts to the entire innovation ecosystem, by fostering more start-up creation and VC investment in many niches of the technology industry.

The adoption of antitrust remedies to avoid that the multitude of big tech start-up acquisitions end up harming innovation in the long-run is highly controversial, however. As argued by Professor Erik Hovenkamp in U.S. Department of Justice (2020), if it is just too hard to compete against the big techs because of high network effects or data and AI capabilities, this should not be considered a competition policy issue. He explained that antitrust reviews try to figure out what will be the effect on prices in the short-term after an acquisition. But, just after the acquisition of a start-up by a big tech nothing is going to happen, because the start-up is too small yet. What should be concerned, according to him, is the impact of such acquisitions on the trajectory of the market, as they may kill or hinder the emergence of a start-up that would be the new big tech.

Gilbert (2021) suggests that a mix of antitrust enforcement and regulatory measures should be considered. For example, interoperability and data portability measures would be easily implemented even by small start-ups, creating means for more start-ups to develop killer, disruptive, innovative solutions that compete against big incumbent players. In fact, well-funded start-ups, with access to data and great AI tools, should have good chances to succeed, ensuring that the digital economy continues to generate high and long-lasting levels of investments and innovation to support economic development and welfare increases.

7. Summary and Conclusion

In this paper, we analyzed the effects of startup acquisitions made by the big techs in the past decade on innovation incentives in different industry segments. Our empirical strategy was based on assessing the effects of big tech start-up acquisitions on venture capital activity, as the innovation literature suggests a causal relationship between VC investment and increases in innovation rates. Using a dataset of more than 32,000 venture

capital deals, almost 400 tech start-up acquisitions, as well as thousands of IPOs and M&As of VC-backed start-ups consummated worldwide between 2010 and 2020 by Google, Facebook, Amazon, Apple, and Microsoft in more than 170 industry segments, we examined the effects of big tech start-up acquisitions on venture capital activity with two alternative estimation approaches.

First, we employed a two-way fixed effects Poisson estimation for identifying semi-elasticities of VC activity with respect to big tech start-up acquisitions. Second, we estimated contemporaneous and future causal average treatment effects of big-tech start-up acquisitions on venture capital activity in the industry segment that received such acquisitions. The second approach used a new dynamic differences-in-differences setup that allows staggered treatment effects and switching treatment status, proposed by Imai, Kim, and Wang (2020).

Our results provide robust ground for challenging claims about the existence of measurable negative effects of big tech start-up acquisitions on VC activity. Instead, causal, statistically significant positive effects were found even when we control for other exit events, like IPOs and M&As that may also affect venture capital activity. For example, after controlling for other factors that may impact VC activity, like IPOs and other mergers and acquisitions M&As, we found an average increase of 30.7% in the total amount of VC funding towards U.S. based start-ups in the four quarters following a big tech start-up acquisition. Also, for deals targeting European start-ups, we found a causal, statistically significant increase of 32.1% in the level of VC funding on the treated industry segments in the first quarter after the treatment.

On the other hand, our results do not suggest that one should foster big tech start-up acquisitions in support of innovation. Although big techs' intensive acquisition strategy may have a median socially positive outcome, as they foster innovation through increased

venture capital activity, the mean effect may not be positive, as acquisitions may eliminate competition.

Our findings showed that such positive effects of big tech start-up acquisitions on VC activity, when existent, persist for a few months only, and so may not have persistent, long-term impacts on the innovation incentives in the the start-up ecosystem. At the same time, these results challenge claims about the existence of negative impacts of these acquisition on innovation due to the creation of “kill zones” for start-ups, and should inform current competition policy discussions on imposing restrictions on acquisitions of start-ups by the big techs. For example, our results suggest that exit through acquisition is an important incentive for venture investment, and making it more difficult by blocking big tech start-up acquisitions may end up resulting in less VC investment to support innovation.

An aspect that deserves further investigation are the 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. Future research should also find relevant analysing data of venture capitalists’ individual investment decisions in order to investigate whether big techs start-up acquisitions make them more or less likely to invest in start-ups of the same industry segments.

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Table A1 – Detailed results of the two-way fixed effects Poisson estimation – Worldwide

	(1)	(2)	(3)	(3.F)	(4)	(5)	(6)	(6.F)
main								
plat	0.0298 (0.0317)	0.0183 (0.0318)	0.0229 (0.0279)	0.0240 (0.0281)	0.0279 (0.0762)	0.0187 (0.0759)	0.0197 (0.0751)	0.0331 (0.0725)
L.plat	0.0627 (0.0411)	0.0509 (0.0397)	0.0474* (0.0259)	0.0459* (0.0251)	0.0734 (0.0725)	0.0698 (0.0792)	0.0712 (0.0781)	0.0801 (0.0799)
L2.plat	0.0812** (0.0346)	0.0711** (0.0338)	0.0704*** (0.0197)	0.0679*** (0.0200)	0.195* (0.113)	0.198* (0.110)	0.198* (0.110)	0.195* (0.106)
L3.plat	0.0668** (0.0309)	0.0616* (0.0323)	0.0610*** (0.0207)	0.0577*** (0.0212)	0.148* (0.0844)	0.119 (0.0839)	0.117 (0.0829)	0.133 (0.0814)
F.plat				0.0111 (0.0268)				0.125 (0.0990)
ipo		0.0240*** (0.00824)	-0.00192 (0.00864)	-0.00272 (0.00914)		0.00610 (0.0331)	0.00424 (0.0346)	0.000770 (0.0411)
m&a		0.0133** (0.00623)	-0.00555 (0.00445)	-0.00504 (0.00441)		-0.00398 (0.0218)	-0.00445 (0.0209)	-0.00552 (0.0201)
L.ipo		0.00504 (0.0125)	-0.0223** (0.00993)	-0.0264*** (0.00982)		0.0504* (0.0272)	0.0503* (0.0276)	0.0406 (0.0296)
L2.ipo		0.0115 (0.00850)	-0.0147** (0.00716)	-0.0136* (0.00765)		0.00879 (0.0163)	0.00677 (0.0167)	0.00494 (0.0164)
L3.ipo		0.00330 (0.0153)	-0.0201* (0.0115)	-0.0210* (0.0119)		0.00587 (0.0285)	0.00518 (0.0289)	0.0152 (0.0289)
F.ipo				0.00118 (0.00873)				0.0398* (0.0241)
L.m&a		0.00853 (0.00524)	-0.0103** (0.00442)	-0.0101** (0.00448)		-0.00762 (0.0139)	-0.00744 (0.0136)	-0.00620 (0.0160)
L2.m&a		0.00325 (0.00618)	-0.0143*** (0.00419)	-0.0158*** (0.00402)		0.0148 (0.0118)	0.0149 (0.0120)	0.0111 (0.0127)
L3.m&a		-0.00128 (0.00613)	-0.0166*** (0.00463)	-0.0166*** (0.00455)		0.0257 (0.0182)	0.0251 (0.0186)	0.0119 (0.0215)
F.ma				0.00125 (0.00320)				-0.00399 (0.0268)
L.vcdeals			0.0134*** (0.00157)	0.0140*** (0.00160)				
L2.vcdeals			0.0107*** (0.00175)	0.00985*** (0.00167)				
L3.vcdeals			0.00701*** (0.00186)	0.00672*** (0.00188)				
L4.vcdeals			0.00573*** (0.00175)	0.00568*** (0.00184)				
L.vcfund							0.0000313 (0.0000432)	0.0000192 (0.0000442)
N	7093	7093	6920	6747	7093	7093	7093	6920

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 A2 – Detailed results of the two-way fixed effects Poisson estimation – U.S.

	(1)	(2)	(3)	(3.F)	(4)	(5)	(6)	(6.F)
main								
plat	0.0205 (0.0340)	0.00550 (0.0325)	0.0161 (0.0263)	0.0158 (0.0274)	0.0823 (0.0677)	0.0492 (0.0634)	0.0317 (0.0604)	0.0216 (0.0646)
L.plat	0.0971** (0.0398)	0.0789** (0.0360)	0.0786*** (0.0245)	0.0722*** (0.0241)	0.0999*** (0.0346)	0.0782** (0.0347)	0.110** (0.0474)	0.0793* (0.0481)
L2.plat.	0.125*** (0.0351)	0.104*** (0.0345)	0.0847*** (0.0262)	0.0840*** (0.0264)	0.306*** (0.111)	0.283*** (0.106)	0.147** (0.0608)	0.140** (0.0606)
L3.plat.	0.0606 (0.0410)	0.0506 (0.0398)	0.0310 (0.0307)	0.0318 (0.0317)	0.195* (0.102)	0.160 (0.0984)	0.0179 (0.0564)	0.0173 (0.0554)
F.plat				0.0106 (0.0372)				0.124 (0.102)
ipo		0.0288 (0.0185)	0.00446 (0.0178)	0.00468 (0.0195)		-0.0364 (0.0339)	-0.0306 (0.0331)	-0.0350 (0.0275)
ma		0.00791 (0.00777)	-0.0103* (0.00575)	-0.00953* (0.00541)		0.0112 (0.0151)	-0.000506 (0.0142)	-0.00286 (0.0136)
L.ipo		0.00136 (0.0268)	-0.0160 (0.0227)	-0.0138 (0.0245)		0.0163 (0.0535)	0.0252 (0.0507)	0.00729 (0.0525)
L2.ipo		-0.0183 (0.0192)	-0.0181 (0.0154)	-0.0151 (0.0149)		-0.0340 (0.0527)	-0.0139 (0.0493)	0.00184 (0.0535)
L3.ipo		0.00135 (0.0186)	0.0138 (0.0182)	0.0105 (0.0195)		0.0339 (0.0430)	0.0681* (0.0400)	0.0688 (0.0444)
F.ipo				0.0174 (0.0167)				-0.00292 (0.0334)
L.ma		0.0189*** (0.00722)	0.00284 (0.00737)	0.00490 (0.00736)		0.0175 (0.0136)	0.00241 (0.0102)	0.00310 (0.00994)
L2.ma		0.0120** (0.00607)	-0.00474 (0.00608)	-0.00915 (0.00567)		0.0177 (0.0129)	0.00927 (0.0143)	-0.0105 (0.0153)
L3.ma		0.000377 (0.00689)	-0.0109** (0.00535)	-0.00914* (0.00538)		0.0159 (0.0173)	0.0104 (0.0182)	0.0148 (0.0186)
F.ma				0.00285 (0.00471)				0.0116 (0.0131)
L.vcdeals			0.0193*** (0.00287)	0.0192*** (0.00282)				
L2.vcdeals			0.0147*** (0.00324)	0.0143*** (0.00362)				
L3.vcdeals			0.00904*** (0.00303)	0.00823*** (0.00290)				
L4.vcdeals			0.00568** (0.00246)	0.00551** (0.00238)				
L5.vcdeals			0.00469* (0.00242)	0.00417* (0.00246)				
L.vcfund.							0.000190*** (0.0000626)	0.000186*** (0.0000714)
L2.vcfund							0.000447*** (0.000173)	0.000482*** (0.000153)
L3.vcfund							0.000291*** (0.0000904)	0.000289*** (0.0000925)
L4.vcfund							-0.0000706* (0.0000397)	-0.0000806** (0.0000397)
L5.vcfund							-0.0000552 (0.0000822)	-0.0000814 (0.0000896)
N	6519	6519	6201	6042	6519	6519	6201	6042

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 A3 – Detailed results of the two-way fixed effects Poisson estimation – Europe

	(1)	(2)	(3)	(3.F)	(4)	(5)	(6)	(6.F)
main								
plat	-0.0951 (0.120)	-0.0986 (0.120)	-0.0993 (0.123)	-0.168 (0.139)	-0.225 (0.168)	-0.264 (0.169)	-0.259 (0.167)	-0.334* (0.183)
L.plat	0.0646 (0.119)	0.0665 (0.119)	0.110 (0.110)	0.0929 (0.123)	0.680* (0.359)	0.659* (0.374)	0.667* (0.370)	0.656* (0.372)
L2.plat	0.236* (0.143)	0.248* (0.149)	0.310** (0.153)	0.265* (0.137)	0.651** (0.302)	0.666** (0.312)	0.657** (0.316)	0.637* (0.329)
L3.plat	-0.104 (0.140)	-0.0964 (0.147)	-0.0720 (0.143)	-0.130 (0.135)	0.221 (0.377)	0.248 (0.382)	0.241 (0.382)	0.222 (0.401)
F.plat				-0.176 (0.177)				-0.341 (0.223)
ipo		0.0470 (0.0306)	0.00403 (0.0285)	-0.0230 (0.0291)		0.120* (0.0654)	0.117* (0.0667)	0.138** (0.0614)
ma		0.00887 (0.0177)	-0.0164 (0.0147)	-0.0176 (0.0160)		0.0342 (0.0392)	0.0312 (0.0409)	0.0130 (0.0363)
L.ipo		0.0419 (0.0260)	0.0160 (0.0269)	-0.0113 (0.0280)		0.129 (0.106)	0.125 (0.100)	0.147 (0.0924)
L2.ipo		0.0317 (0.0295)	-0.000109 (0.0254)	-0.00562 (0.0274)		0.0273 (0.0643)	0.0170 (0.0656)	0.000490 (0.0655)
L3.ipo		0.000371 (0.0432)	-0.0394 (0.0372)	-0.0545 (0.0418)		0.0827 (0.0628)	0.0775 (0.0622)	0.0662 (0.0592)
F.ipo				-0.0494 (0.0468)				0.0543 (0.0652)
L.ma		-0.00963 (0.0147)	-0.0382** (0.0167)	-0.0480*** (0.0179)		-0.0361 (0.0346)	-0.0410 (0.0356)	-0.0133 (0.0510)
L2.ma		-0.00104 (0.0167)	-0.0398** (0.0162)	-0.0294* (0.0155)		-0.0348 (0.0383)	-0.0391 (0.0389)	-0.0313 (0.0378)
L3.ma		-0.000834 (0.0173)	-0.0328** (0.0157)	-0.0522*** (0.0178)		-0.0261 (0.0270)	-0.0312 (0.0279)	-0.00572 (0.0348)
F.ma				0.0346* (0.0200)				-0.0156 (0.0316)
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)	
N	5494	5494	5494	5280	5494	5494	5494	5280

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 B – List of Sector – Industry – Subindustries

Sector	Industry	Subindustry
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

Sector	Industry	Subindustry
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
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

Sector	Industry	Subindustry
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
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

Sector	Industry	Subindustry
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