Kill Zones? Measuring the Impact of Big Tech Start-up Acquisitions on Venture Capital Activity

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1. Introduction

Concerns about big tech firms' growing dominance, their potential to manipulate digital markets, and their pervasive appropriation of personal data have greatly increased the willingness of national policy makers to regulate digital platforms like Google, Facebook, Apple, Amazon and Microsoft, and the Internet. One widespread belief is that concentration of major digital markets has increased to a level where it harms innovation (e.g., Morton et al, 2019). A related assertion is that they defend their established markets using strategies that will quench innovation. An aggressive strategy of mergers and acquisitions pursued by dominant platforms is one observation that nourish such fears. Another one is alarm about "kill zones" for start-ups that are created by the unlikely success of directly competing against a big and resourceful digital platform. Such reasoning might undermine adoption by customers and reduce interest by venture capitalists, who stay away from funding such start-ups (Kamepalli et al., 2020).

Although there is supporting evidence for both claims, very little systematic work has been done to empirically examine these potentially concerning outcomes, the conditions under which they might materialize, and what might be done to mitigate them. This paper investigates the influence of the five largest U.S. digital platforms on venture capital activity worldwide. It aims to complement the emerging research on platforms' influence on digital innovation and entrepreneurship. Using a rich dataset of more than twenty-five thousand

venture capital deals reported by the consulting firm CB Insights[1], I examine whether big tech's acquisitions affect venture capital flows around the world, channeling innovation in a direction favorable to themselves. More specifically, I use an event-study empirical design with heterogenous treatment timing to investigate the impact of big tech's main acquisitions on the number of deals and on the amount of venture investments driven towards start-ups of more than 170 industry sectors between 2010 and 2019.

By isolating the influence made by digital platforms on the level of VC activity on different industries, I draw conclusions on whether these platforms have biased innovation in the last decade. Also, as the dataset contains information about venture capital deals happened around world, this allowed us to estimate the effect of big tech acquisitions on innovation in different countries and geographic regions and then compare the results. Foreseeable comparisons are how the external shocks impact venture capital activity inside vs. outside the US, in the US, Europe and Latin America, as well as in developed vs. developing countries.

This empirical analysis contributes to the ongoing international debate among policymakers, regulators and researchers on potential benefits and harms created by digital platforms on innovation.

2. Literature Review and Research Questions

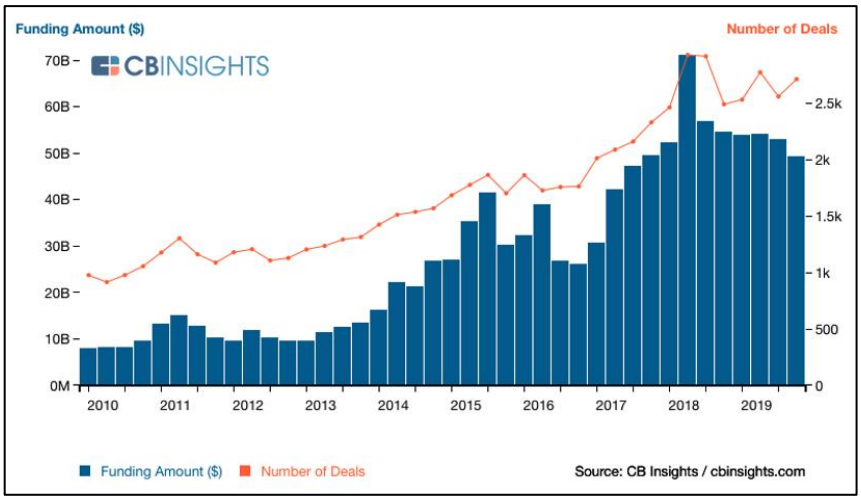
Venture capital is defined as "equity or equity-linked investments in young, privately held companies, where the investor is a financial intermediary who is typically active as a director, an advisor, or even a manager of the firm" (Kortum and Lerner, 1998, p. 3). There is evidence in the research literature of a close relationship between innovation and venture

[1] https://www.cbinsights.com

capital. Robust empirical evidence supports a positive, causal association between venture capital activity and patenting activity (Kortum and Lerner, 2000; Da Rin & Pensas, 2007, Faria & Barbosa, 2014). Recent studies have also supported the key role played by venture capital in enabling small and medium-sized start-ups, innovation and growth (Imarhiagbe et al., 2019).

Venture capital investment is usually categorized by series A to E in accordance with the growth states of the targeted firm. 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 stablished a consistent performance record, like a growing user base, positive cash-flow, and sales growth, it may seek venture capital to bootstrap. As a strategy to mitigate risks, venture capitalists follow a staged capital infusion mechanism (Gompers & Lerner, 2001). The first round of venture capital a firm receives is identified as a Series A investment. Following rounds may happen, and if so, they 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. Figure 1 presents the evolution of the number of VC deals and funding between 2010 and 2019. The graph shows a clear positive time-trend in the venture capital activity until 2018, when it seems to have reversed to a slow decreasing movement.

Figure 1 - Distribution of deals and funding per quarter along the last 10 years

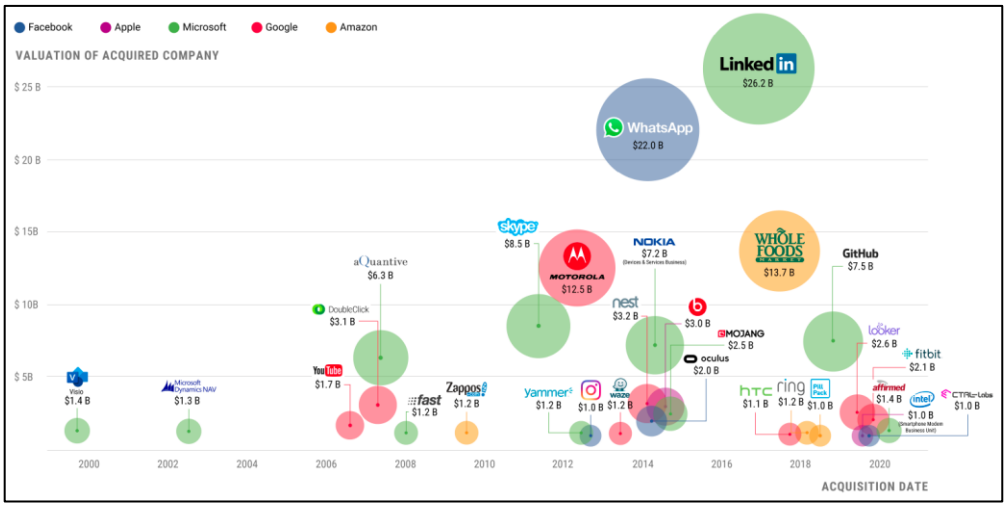


Informational asymmetries and uncertainties frequently are associated with start-up activity. As in any risk-seeking financial activity, however, venture capitalists presumably want to make informed and rational investment decisions that maximize expected profits. Giving a plethora of start-up firms from various industry sectors, venture capitalists' constraints to take investment decisions are reportedly more related to factors like time to scrutinize firms and expertise on their industry niche, among others, rather than cash availability (Gompers & Lerner, 2001; Sorensen, 2007). Indeed, according to the same authors, in order to maximize expected profits, VCs investment decisions take into consideration micro aspects of targeted start-up firms, like the quality of their management team and the level of competition in its industry niche. Lerner (1995) also 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.

In the last 20 years, the big techs have been intensive in acquiring promising start-ups in their early stages of development (see Figure 2), a strategy to defend their established

markets that may quench innovation. Indeed, some authors have alarmed for the creation of "kill zones" for start-ups due to their unlikely success of directly competing against a big and resourceful digital platform. Such reasoning might undermine adoption by customers and reduce interest by venture capitalists, who stay away from funding such start-ups (Kamepalli et al., 2020). Others, on the other hand advocate that big acquisitions made by these digital platforms actually attract more funding for startups playing in the same segment, as if the big tech's bet on it gives positive signs of the potential of growth and profit in the segment (Foerderer et al., 2018).

Figure 2 – Billion-dollar big-tech acquisitions in the last 20 years



Source: CB Insights (2020)

In fact, big-techs reputation, wide and diverse market presence, paragon investments in R&D, and reportedly intense start-up acquisition activity along the last ten years lead us to question whether they significatively affects VC funding, and consequently innovation, towards or away from specific industry niches. A second more narrowly construed question, worthy to be investigated as it may inform innovation policy around the world, is whether such effects differ significatively inside and outside the U.S. The next section presents the

empirical research design and summarizes the dataset. Section 4 present and discuss the main findings. Section 5 concludes.

3. Research Design

In order to answer these research questions, I rely on an event-study empirical design with heterogenous treatment effects (Goodman-Bacon, 2018; Athey and Imbens, 2018; Sun and Abraham, 2020), similar to the empirical strategy employed by Abeberese et al., (2020) to study heterogenous effects of political changes on firm's productivity in Indonesia. I estimate average treatment effects by using a setting with panel data of annual number of deals and amount of venture-capital funding towards start-ups in different industries from 2010 to 2019. Some of these industries are subjected to external shocks in different timings, considered as multi-million start-up acquisitions made by Amazon, Facebook, Microsoft, Google and Apple, which may attract or repeal VC funding to the industries related with the acquired start-ups.

3.1. Estimation method

The estimation strategy exploits the quasi-random heterogeneity in the timing of the external shocks (a multi-million acquisition of a startup made by one of the big techs) received by different industries. For such, consider that start-ups playing in industry niche $i \in I$ of economic sector $s \in S$ receive in each time $t \leq T$ a total amount of venture-capital funding ($VC\_Funding_{i,s,t}$), through a $VC\_Deals_{i,s,t}$, total number of deals, to support the creation and delivery of innovative products and services. Also consider that a quasi-random external shock happens in industry $k \in I$ in time $h_k \leq T$. To measure the effect of the external

shocks on all industries, we first estimate a traditional two-way fixed-effects differences-in-differences (DiD) model, specified by equation (1). So, we are investigating within-industry changes in venture capital activity following multi-million big tech's startup acquisitions.

$$\log(Y_{i,s,t}) = \alpha_0 + \beta Post_{i,t} + c_i + \delta_{s,t} + u_{i,s,t} \qquad (1)$$

In equation (1), we assume that the natural logarithm of the total amount of funding per industry and per year, and of the natural logarithm of the total number of deals per industry and per year (both generally represented by the output variable $Y_{i,s,t}$) are dependent on a treatment indicator variable ($Post_{i,t}$), that equals 1 when $i = k$ and $h_k \leq t \leq T$. We also include sector-year fixed-effects ($\delta_{s,t}$), to control for shocks that affect the venture capital activity of all industries within a same sector in a given year. Moreover, we control for time-invariant industry-specific heterogenous characteristics that may affect the level of venture capital activity in each industry (c_i).

However, recent econometric research has shown that traditional DiD approaches produce biased estimates in the presence of heterogenous shocks over time (Abraham and Sun, 2018). They also argue that the two main identification assumptions in event study designs (the existence of pre-treatment parallel trends and the requirement of no anticipation of treatment effects) cannot be assessed under the traditional DiD design. So, the authors propose, instead, the use of event study specification, where we estimate a full-dynamic model. Equation (2) specifies such model to assess the identification assumptions of pre-treatment parallel trends among the industries and no treatment-anticipation effects.

$$\log(Y_{i,s,t}) = \alpha_0 + \sum_{\tau=-3}^{-2} \beta_\tau \mathbf{1}(years\ since\ shock = \tau) + \sum_{\tau=0}^{3} \beta_\tau \mathbf{1}(years\ since\ shock = \tau) + c_i + \delta_{s,t} + u_{i,t} \qquad (2)$$

Equation (2) expands equation (1) by including pre-treatment and post treatment dummies to measure any effect of quasi-random external shocks in the years before the shock, in the year of the shock, as well as in the years after the shock. $\mathbf{1}(years\ since\ shock = \tau)$ is a dummy variable equal to one to industry *i=k* if year t is τ years before or after the year when industry *k* received the shock (h_k). In our estimation, as our analysis comprises 10 years of data, we included dummies for the three years before and after the treatment, with periods before or after this window binned in its extreme values ($\tau = -3$ and $\tau = 3$). Also, we omitted a dummy variable for $\tau = -1$, which is, then, considered the baseline year.

With this setup we can measure the effect of the shock in each year that surrounds the year of the shock, what allows the analysis of the identification assumptions. However, Borusyak and Jaravel (2018) explains that such full-dynamic model is underidentified, because of the presence of industry and time fixed effects. These authors suggest dropping not only one pre-trend term, as done in equation (2), but also the earliest pre-trend term, what in our model is $1(years\ since\ shock = -3)$, and then assess a null hypothesis that the remaining pre-treatment coefficients are statistically different than zero. A failure in rejecting this null hypothesis would confirm the existence of parallel trends and then allow the use of a semi-dynamic specification, where all pre-treatment coefficients are set to zero, as it can be seen in equation (3).

$$\log(Y_{i,s,t}) = \alpha_0 + \sum_{\tau=0}^{3} \beta_\tau \mathbf{1}(years\ since\ shock = \tau) + c_i + \delta_{s,t} + u_{i,t} \qquad (3)$$

3.2. The dataset

The analysis relies on information about several big start-up acquisitions made by the Google, Facebook, Amazon, Apple, and Microsoft between 2010 and 2019. While dozens of small companies were acquired by such digital platforms in the last ten years, the analysis consider eleven start-up acquisitions as external shocks potentially affecting VC activity on their industry niches. Table 1 lists the acquisitions considered in this analysis.

Table 1 – Big tech acquisitions considered in the analysis

Year	Platform	Acquired Company	Valuation (million US$)	Industry	Sector	Country
2011	Google	ITA Software	700	IT Services	Computer Hardware & Services	United States
2011	Microsoft	Skype	8500	Telecom Services	Mobile & Telecommunications	Luxembourg
2012	Amazon	Kiva Systems	775	Machinery & Equipment	Industrial	United States
2012	Facebook	Face.com	100	Scientific, Engineering Software	Software (non-internet/mobile)	United States
2014	Facebook	Oculus VR	2000	Gaming	Software (non-internet/mobile)	United States
2014	Facebook	WhatsApp	22000	Mobile Software & Services	Mobile & Telecommunications	United States
2014	Google	Nest Labs	3200	Consumer Electronics	Consumer Products & Services	United States
2017	Amazon	Whole Foods Market	13700	Grocery	Retail (non-internet/mobile)	United States
2017	Amazon	Souq.com	580	eCommerce	Internet	United Arab Emirates
2018	Amazon	PillPack	1000	Pharmaceutical Distribution & Wholesale	Healthcare	United States
2018	Apple	Texture	485	Mobile Commerce	Mobile & Telecommunications	United States

Besides the use of information about big tech acquisitions in the last years, I rely on data of venture capital deals collected by the startup CB Insights to estimate the aforementioned models.[2] This database contains approximately twenty-five thousand venture

[2] https://www.cbinsights.com

capital deals that took place between 2010 to 2019 whose value exceeded $7.5 million[3]. The dataset contains several information about each deal, like the name of the start-up funded, its economic sector and specific industry, its location (continent, country, state and city), amount funded, type of the investment round (Series A to E), day, month and year of the deal, among others. Funded startups are categorized among nineteen economic sectors (e.g., Internet, Healthcare, Consumer Products and Services, etc.) and 175 industries niches (e.g., IT Services, Telecom Services, Gaming, Grocery, etc.). Annexes I and II contain summary statistics of the dataset.

This data set represents 40% of the total number of venture capital deals in this period and 92% of the total value of $1.1 trillion funded by venture capitalists during the same period. The analysis is limited to a subset of data due to use conditions imposed by CB Insights. Whereas the focus on the upper half of the number of deals limits the analysis in some extent, it has the benefit of avoiding including very small deals in the estimation. Also, as our output variable is the total amount funded by industry over the time, the dataset leaves few VC dollars behind (around 8% of the total amount funded).

For estimating the models, three panel datasets were considered. The first one includes deals that happened in the 2010-2019 period in all the 11 treated industries (those that receive the shocks, or the big tech acquisitions), as well as in all the other 164 non-treated industries. Panel two includes deals that happened in the same period in all treated industries, as well as in other 72 industries that are not in the same economic sector of the industries which received the shock. Finally, the third panel includes deals that happened in the same 2010-2019 period in all treated industries, as well as in all the 92 other non-treated industries

[3] Median of the value funded per deal, calculated among all venture capital deals from 2010 to 2019.

categorized within the same economy sector of the industries which received the shock. Panels two and three are important to test pre-treatment parallel trends identification assumption.

Also, I built those three panel datasets i) including all deals, ii) deals targeting startups based outside the U.S., iii) and deals targeting startups based inside the U.S, what let us with a total of nine panel datasets for estimating the models, important to identify effects of big tech acquisitions on very dynamic and VC-active markets like the U.S., which attracts more than half of the VC funding worldwide, as well as effects on countries with relatively low VC activity. Table 1 bellow present summary statistics of three panel datasets including all deals (both US-based and non-US-based). Summary statistics of the other panel datasets are omitted for brevity.

Table 2 – Summary statistics of Panels 1, 2 and 3 including all VC deals

Panel 1 – All industries

Variable	Obs	Mean	Std. Dev.	Min	Max
log_fund_vc	1,750	3.175089	2.581408	0	11.1382
log_vc_deals	1,750	1.201363	1.28083	0	7.233455

Panel 2 – Treated industries + non-treated industries (other sectors)

Variable	Obs	Mean	Std. Dev.	Min	Max
log_fund_vc	830	3.232167	2.65993	0	10.17354
log_vc_deals	830	1.205183	1.283574	0	6.073044

Panel 3 – Treated industries + non-treated industries (same sectors)

Variable	Obs	Mean	Std. Dev.	Min	Max
log_fund_vc	1,030	3.437342	2.681796	0	11.1382
log_vc_deals	1,030	1.381819	1.436731	0	7.233455

In the next section I present and discuss the main results of the estimation for each of the three panels for all VC deals, VC deals targeting non-US startups, and US-only startups.

4. Results

We present results for the effects of big tech's acquisitions on the amount of VC funding per industry, as well as on the number of VC deals per industry. Such effects are estimated for the three panel datasets described in Section 3. First, Table 3 presents results from the estimation of the DiD model specified in Equation (1). The results suggest that big-tech's acquisitions attract more venture capital investment (in total funding and total number of deals) for startups in the same industries of the acquired start-ups, and that such effect is greater for startups based outside the U.S when compared with those based inside the U.S.

Table 3 – Panel 1: Results of the differences-in-differences estimation

	Log[Total VC funding]			Log[Total VC deals]		
VARIABLES	ALL	Non-US	US	ALL	Non-US	US
post	0.929**	1.237**	0.805*	0.712***	0.725***	0.594***
	(0.459)	(0.498)	(0.409)	(0.200)	(0.265)	(0.185)
N	1750	1650	1550	1750	1650	1550
adj. R-sq	0.266	0.318	0.166	0.310	0.354	0.176

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

However, as already discussed in Sub-section 3.1, traditional DiD specification may result in biased coefficients when we have heterogenous treatments effects over time. Therefore, as suggested by recent econometric research, we estimated fully dynamic models, as specified in equation (2). The resultant estimates are detailed in Table 4. They show that, in general, the effect of big-tech's acquisitions on the level of VC activity of treated industries is not statistically different than zero either in years preceding the treatment or in years following the treatment for most of the case.

However, as shown by Borusyak and Jaravel (2018), the fully dynamic model is underidentified in the presence of both industry and time fixed effects. Then, we followed the procedure proposed by these authors and re-estimate the fully dynamic model also dropping the dummy variable $1(years\ since\ shock = -3)$. With this approach, we find pre-trend terms statistically non-significant (see Table 5), what supports our identification assumptions of pre-treatment parallel trends and no anticipation of treatment effects. Such results suggest that a semi-dynamic model, as the one specified in equation (3), should be preferable to

Table 4 – Panel 1: Results of the fully-dynamic estimation

	Log[Total VC funding]			Log[Total VC deals]		
VARIABLES	ALL	Non-US	US	ALL	Non-US	US
t=-3 years	-0.988*	-0.693	-1.072	-0.528	-0.424	-0.575
	(0.551)	(0.741)	(0.842)	(0.326)	(0.364)	(0.386)
t=-2 years	0.0203	-0.189	-0.260	-0.329*	-0.262	-0.403**
	(0.527)	(0.617)	(0.491)	(0.186)	(0.177)	(0.192)
t=0 years	-0.0302	0.390	-0.467	0.0921	0.115	-0.0354
	(0.475)	(0.723)	(0.526)	(0.195)	(0.238)	(0.193)
t=1 year	0.320	0.657	0.160	0.395*	0.308	0.224
	(0.532)	(0.663)	(0.360)	(0.204)	(0.278)	(0.136)
t=2 years	0.882	1.220	0.429	0.403*	0.531*	0.227
	(0.725)	(0.790)	(0.610)	(0.243)	(0.279)	(0.226)
t=3 years	0.893	1.300	0.919	0.667*	0.871**	0.518
	(0.731)	(0.812)	(0.651)	(0.393)	(0.399)	(0.348)
N	1750	1650	1550	1750	1650	1550
adj. R-sq	0.267	0.318	0.169	0.316	0.364	0.184

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

Table 5 – Panel 1: testing of the identification assumptions

	Log[Total VC funding]			Log[Total VC deals]		
VARIABLES	ALL	Non-US	US	ALL	Non-US	US
t=-2 years	0.675	0.270	0.415	0.0203	0.0186	-0.0405
	(0.578)	(0.659)	(0.566)	(0.221)	(0.225)	(0.241)
t=0 years	0.604	0.834	0.186	0.431*	0.387	0.315
	(0.522)	(0.553)	(0.519)	(0.219)	(0.262)	(0.237)

t=1 year	0.946*	1.096*	0.801*	0.729***	0.577*	0.569***
	(0.499)	(0.569)	(0.411)	(0.204)	(0.296)	(0.183)
t=2 years	1.445**	1.616**	0.986	0.704***	0.774***	0.527***
	(0.721)	(0.701)	(0.598)	(0.166)	(0.269)	(0.178)
t=3 years	1.411**	1.665**	1.450**	0.943***	1.094***	0.803***
	(0.671)	(0.730)	(0.591)	(0.320)	(0.367)	(0.284)
N	1750	1650	1550	1750	1650	1550
adj. R-sq	0.266	0.318	0.167	0.312	0.362	0.179

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

On the other hand, considering that Panel 1 includes treated industries as well as all non-treated industries, one could argue that the pre-treatment parallel trends assumption, although supported when the analysis consider the full set of industries, should not hold when we compare treated industries with non-treated industries strongly different, as the ones from different economic sectors, for example. Thus, we re-tested the identification assumptions by estimating the fully dynamic model dropping the dummy variables dropping the dummy variable $1(years\ since\ shock = -1)$ and $1(years\ since\ shock = -3)$ and using the Panel 2, which includes data from treated industries and non-treated industries of economic sectors that did not receive any treatment.

The results, presented in Table 6, do not allow us to confidently support the identification assumptions, as they show some statistically significant pre-treatment coefficients. Such findings suggest that non-treated industries of economic sectors that did not receive any treatment should not be useful to identify the treatment, as they may not present pre-treatment parallel trends with respect to the treated industries. Thus, we repeated the same procedure for testing the identification assumptions but using Panel 3, which includes treated industries and non-treated of the same economic sectors of the treated ones. The results, presented in Table 7, show that the identification assumptions are supported for Panel 3,

which becomes, then, our preferred panel dataset for estimating the effects of big tech's acquisitions on the level of venture capital activity on different industries.

Table 6 – Panel 2: testing of the identification assumptions

	Log[Total VC funding]			Log[Total VC deals]		
VARIABLES	ALL	Non-US	US	ALL	Non-US	US
t=-2 years	-0.223	-0.424	0.541*	0.173*	0.433***	0.135
	(0.157)	(0.365)	(0.311)	(0.100)	(0.135)	(0.157)
t=0 years	-1.165***	-1.431**	-1.036***	-0.308	-0.582	-0.166
	(0.357)	(0.562)	(0.343)	(0.233)	(0.359)	(0.172)
t=1 year	-1.377***	-1.804***	-0.645	-0.0385	-0.243	0.0636
	(0.415)	(0.528)	(0.660)	(0.314)	(0.304)	(0.302)
t=2 years	-1.892***	-1.280	-1.653**	-0.444	-0.256	-0.440
	(0.555)	(0.814)	(0.648)	(0.389)	(0.432)	(0.297)
t=3 years	-3.058***	-3.374**	-2.497**	-1.397*	-1.499**	-1.037
	(1.015)	(1.288)	(1.140)	(0.779)	(0.715)	(0.682)
N	830	780	710	830	780	710
adj. R-sq	0.300	0.353	0.185	0.403	0.475	0.245

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

Table 7 – Panel 3: testing of the identification assumptions

	Log[Total VC funding]			Log[Total VC deals]		
VARIABLES	ALL	Non-US	US	ALL	Non-US	US
t=-2 years	0.675	0.270	0.415	0.0203	0.0186	-0.0405
	(0.574)	(0.653)	(0.560)	(0.220)	(0.223)	(0.239)
t=0 years	0.604	0.834	0.186	0.431*	0.387	0.315
	(0.519)	(0.548)	(0.514)	(0.218)	(0.260)	(0.235)
t=1 year	0.946*	1.096*	0.801*	0.729***	0.577*	0.569***
	(0.495)	(0.564)	(0.407)	(0.202)	(0.293)	(0.181)
t=2 years	1.445**	1.616**	0.986*	0.704***	0.774***	0.527***
	(0.715)	(0.695)	(0.592)	(0.165)	(0.266)	(0.176)
t=3 years	1.411**	1.665**	1.450**	0.943***	1.094***	0.803***
	(0.666)	(0.724)	(0.585)	(0.317)	(0.364)	(0.281)
N	1030	980	940	1030	980	940
adj. R-sq	0.247	0.307	0.140	0.288	0.350	0.167

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

With the information included in Panel 3, we estimated both the traditional DiD model, the fully dynamic model, and the semi-dynamic model. Detailed results of the DiD model and of the fully dynamic model are omitted for brevity, as these models do not produce consistent estimates. The results of the semi-dynamic estimation, which is the most suitable model, as the identification assumptions hold for Panel 3, are presented in Tables 8.

Table 8 – Panel 3: Results of the differences-in-differences estimation

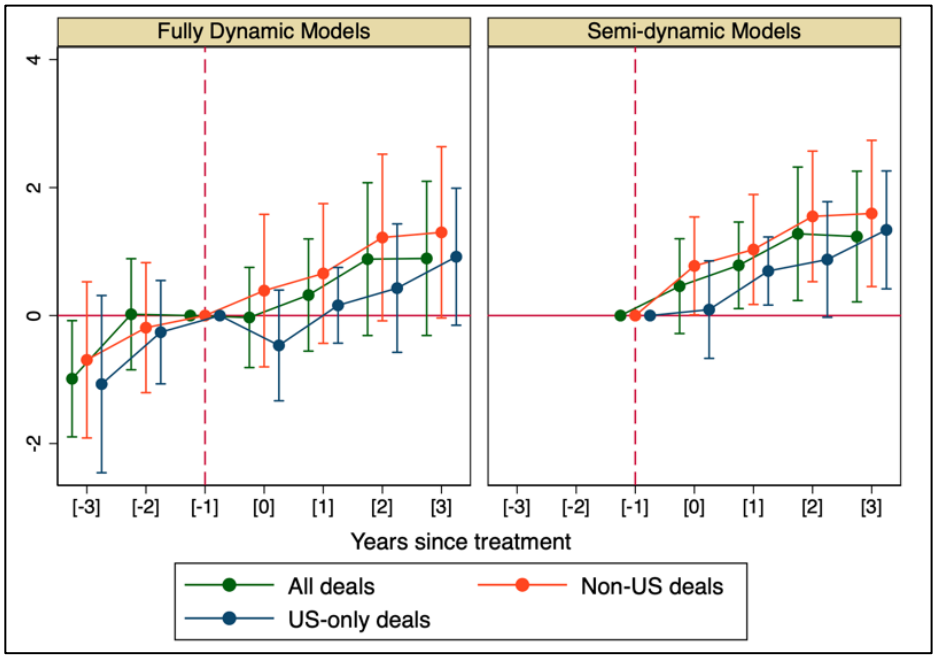
	Log[Total VC funding]			Log[Total VC deals]		
VARIABLES	ALL	Non-US	US	ALL	Non-US	US
t=0 years	0.459	0.776*	0.0925	0.426**	0.383	0.324
	(0.446)	(0.461)	(0.459)	(0.192)	(0.232)	(0.203)
t=1 year	0.785*	1.032**	0.696**	0.724***	0.572**	0.579***
	(0.407)	(0.517)	(0.320)	(0.175)	(0.262)	(0.151)
t=2 years	1.278**	1.549**	0.876	0.699***	0.769***	0.537***
	(0.628)	(0.614)	(0.544)	(0.161)	(0.249)	(0.161)
t=3 years	1.234**	1.595**	1.338**	0.938***	1.089***	0.814***
	(0.615)	(0.688)	(0.554)	(0.325)	(0.357)	(0.282)
N	1030	980	940	1030	980	940
adj. R-sq	0.246	0.308	0.141	0.289	0.351	0.168

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

The results suggest that venture capitalists are attracted by platform acquisitions, as the average amount of VC funding and the total number of VC deals in industries that received the shock increase significatively in post-acquisition years. Considering all the VC deals (columns 1 and 4 of Table 8), the post-treatment amount of VC funding and the total number of VC deals in industries that receive the shock are in average 200 % and 120 % greater than in industries that did not receive the shocks but that are in the same economic sector, even in

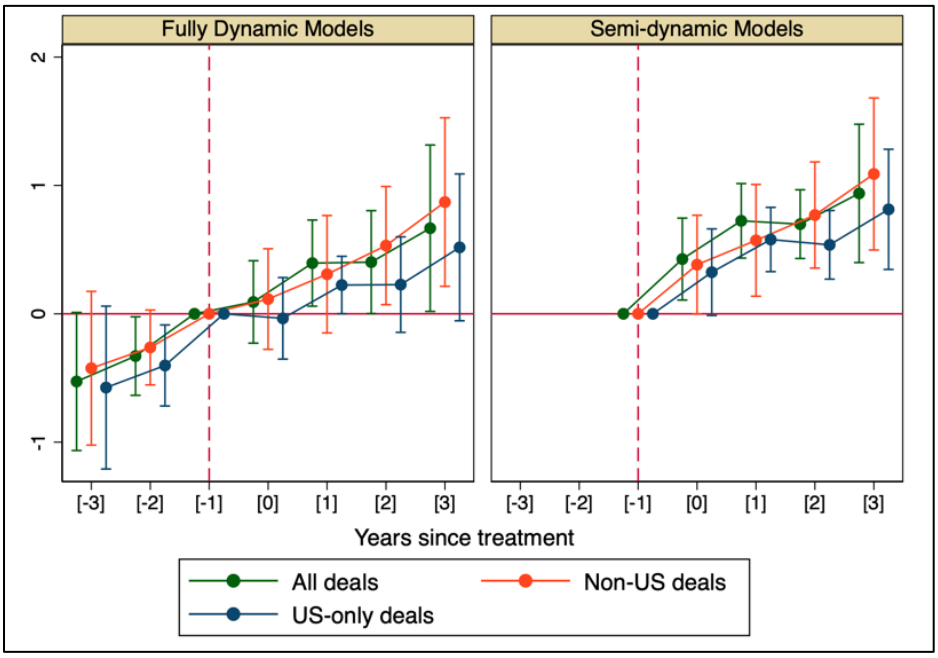
the presence of an intercept, and controlling for industry and time-sector fixed effects.[4] Another interesting aspect is that the level of venture capital activity does not present a statistically significant increase in the same year of the acquisitions, as venture capital deals take months to be setup and closed. Also, the effects seem to grow year by year, although we cannot affirm that they are statistically different among each other. Figures 1 and 2 bring a visual representation of the magnitudes and confidence intervals of the coefficients produced by the estimation of the fully dynamic and of the semi-dynamic models.

Figure 1 – Panel 3: Effects of big-tech's acquisitions on the total amount of VC funding in treated industries



[4] The calculation of the average effects was done my averaging the coefficient estimates obtained by years t=1, t=2 and t=3. Such average was, then, exponentiated, subtracted one unit, and finally multiplied by 100, procedure that resulted in the percentual difference between treated and non-treated industries in the years that follow the external shocks.

Figure 2 – Panel 3: Effects of big-tech's acquisitions on the total number of VC deals in treated industries



The results also suggest that the effect of big tech's acquisitions is greater on venture capital activity outside the U.S. than inside the U.S. Indeed, when considered only venture capital deals targeting startups based outside the U.S., the post-treatment total amount of VC funding and the total number of VC deals in industries that receive the shock are in average 301% and 125% greater than in industries that did not receive the shocks but that are in the same economic sector. When we just consider VC deals and VC funding to US-based startups, such effects are of 164 % and 90%, instead.

Such differences may be explained by the existence of highly dynamic venture capital activity in the U.S., where VC investors have more information and means to decide about allocation of venture funding without relying too much on acquisitions made the big techs. Contrarily, in other countries (may be with an exception to China), venture capitalists have

fewer local references and deals to help them identifying trends and industries potential for growth, what end up making them more dependent on big bets made by well-known digital platforms in specific industries.

5. Conclusion

In this research we measured the effects of multi-million startup acquisitions made by the big techs in the past decade on venture capital activity in different industry segments. By using a modern event-study research design, we could demonstrate that venture capital activity is significantly affected by acquisitions made by the big-techs, and that the magnitude of such effects are higher outside the U.S. Some authors have suggested the existence of "kill zones for innovation", that are industry segments in which the presence and strategic interests of digital platforms discourage venture investments from other venture capitalists (Hylton, 2019; Kamepalli et al., 2020). For deals above $7.5 million, our analysis at the industry level does not support such a claim. Instead, it shows a persistent positive impact of the startup acquisitions made by digital platforms on the appetite of venture capitalists to also invest in startups of such industries. These results corroborate other research that found positive impacts of platforms acquisitions and venture capital investments on innovation (e.g., Foerderer et al., 2018).

Such preliminary results may inform future research on whether platforms significatively bias Venture Capital activity, and consequently innovation, towards or away of specific industry niches, as well as how such processes may vary across countries of different geographic regions and with different levels of economic development. I expect that these first empirical findings inform the ongoing international debate among policymakers,

regulators and researchers on potential benefits and harms created by digital platforms on innovation.

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Annex I

Descriptive Statistics of Venture Capital Deals from 2010 to 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
amount	25,081	38.82213	140.9124	7.5	14000
Other Venture	25,081	.0400303	.1960342	0	1
Series A	25,081	.3033771	.4597258	0	1
Series B	25,081	.3071249	.4613108	0	1
Series C	25,081	.1814122	.385367	0	1
Series D	25,081	.0930984	.290576	0	1
Series E+	25,081	.0749571	.2633274	0	1
Africa	25,081	.002472	.0496586	0	1
Asia	25,081	.2366732	.4250485	0	1
Oceania	25,081	.0059806	.0771044	0	1
Europe	25,081	.1261911	.3320713	0	1
North America	25,081	.6226626	.4847301	0	1
South America	25,081	.0060205	.0773595	0	1
2010	25,081	.0453331	.2080379	0	1
2011	25,081	.0605239	.2384597	0	1
2012	25,081	.0563375	.2305768	0	1
2013	25,081	.0634345	.2437476	0	1
2014	25,081	.0890315	.2847949	0	1
2015	25,081	.1113991	.3146319	0	1
2016	25,081	.1080499	.3104496	0	1
2017	25,081	.1331685	.3397636	0	1
2018	25,081	.1648658	.3710668	0	1
2019	25,081	.1678561	.3737459	0	1
1	25,081	.2322076	.4222492	0	1
2	25,081	.2647821	.4412259	0	1
3	25,081	.2580838	.4375891	0	1
4	25,081	.2449264	.4300522	0	1
industry	25,081	99.07675	43.23756	1	175

Annex II

Descriptive statistics of big-tech acquisitions from 2010 to 2019

Variable	Obs	Mean	Std. Dev.	Min	Max
platforms					
Amazon	39	.2307692	.4268328	0	1
Apple	39	.1794872	.3887764	0	1
Facebook	39	.2564103	.442359	0	1
Google	39	.1794872	.3887764	0	1
Microsoft	39	.1538462	.3655178	0	1
industries					
Chips & Semic	39	.1282051	.3386884	0	1
Consumer Elet	39	.1282051	.3386884	0	1
Gaming	39	.025641	.1601282	0	1
Grocery	39	.025641	.1601282	0	1
IT Services	39	.025641	.1601282	0	1
Internet Soft	39	.2307692	.4268328	0	1
Mach & Equip	39	.025641	.1601282	0	1
Mobile Commer	39	.025641	.1601282	0	1
Mobile Softw	39	.1538462	.3655178	0	1
Pharmaceutic	39	.025641	.1601282	0	1
Scient. Engin	39	.0512821	.2234559	0	1
Telecom Devic	39	.0512821	.2234559	0	1
Telecom Serv	39	.025641	.1601282	0	1
eCommerce	39	.0769231	.2699528	0	1
countries					
Finland	39	.025641	.1601282	0	1
Israel	39	.1025641	.3073547	0	1
Luxembourg	39	.025641	.1601282	0	1
Spain	39	.025641	.1601282	0	1
Sweden	39	.025641	.1601282	0	1
Taiwan	39	.025641	.1601282	0	1
United Arab E	39	.025641	.1601282	0	1
United Kindom	39	.0512821	.2234559	0	1
United States	39	.6923077	.4675719	0	1
year					
2011	39	.1282051	.3386884	0	1
2012	39	.1538462	.3655178	0	1
2013	39	.1025641	.3073547	0	1
2014	39	.2051282	.4090739	0	1
2015	39	.025641	.1601282	0	1
2016	39	.025641	.1601282	0	1
2017	39	.1025641	.3073547	0	1
2018	39	.1282051	.3386884	0	1
2019	39	.1282051	.3386884	0	1