The Signaling Value of Technology Venture Acquisitions*

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Abstract: We study the effects of technology venture acquisitions on investment in the acquired firm's business area. Using data on acquisitions and venture capital funding in the U.S. from Crunchbase, we consider the ventures acquired between 2014 and 2016 alongside a set of comparable control ventures that remained independent as of 2016. By modeling each venture as a point in the technology space, we leverage textual analysis to track investments in business areas similar to acquired or control ventures. Our difference-in-differences analysis shows that acquisitions stimulate venture capital investment, particularly in areas with fewer ventures and more intense past or expected acquisition activity. This suggests that tech acquisitions signal the potential of a business area. Contrary to antitrust concerns, we find that acquisitions by big tech platforms and other large acquirers have a similar positive effect, whereas private equity buyouts lead to an even greater increase in venture capital activity.

JEL Codes: G24, L26, L40, O31.

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1. Introduction

Technology ventures play a pivotal role in driving innovation and fostering economic growth. While only a limited number of tech ventures secure venture capital (VC) financing, those that are VC-backed stand out as major contributors to innovation and research and development (R&D) expenditure (Lerner and Nanda 2020). Venture capital has enabled entrepreneurs to establish technology ventures and pursue original ideas, at times achieving a successful exit, either through an Initial Public Offering (IPO) or an acquisition. In the last couple of decades, exits through mergers and acquisitions (M&A) have become more common (Ederer and Pellegrino 2023), to the point that, according to the Silicon Valley Bank Global Startup Outlook Survey, in 2020 58% of US entrepreneurs viewed incumbent buyout as the likely form of exit.[1]

Private markets for ideas or technologies are typically characterized by high degrees of asymmetric information, and the venture capital industry is no exception (Gompers and Lerner 2001; Ozmel, Robinson and Stuart 2013; Howell 2020). Investors look for signals, such as other investors' choices, in discovering the true value of a business area before investing or acquiring in it (Leland and Pyle 1977; Fried and Hisrich 1994). In this context, majority control acquisitions, which typically entail significant financial commitments, may convey a signal about the size and potential of the market for the startup's product or technology, thus reducing information asymmetries and possibly stimulating (or reducing) VC investment and entry (Rasmusen 1988; Phillips and Zhdanov 2013). We refer to these potential mechanisms as the "signaling effect."

However, differently from IPOs, technology venture acquisitions not only influence entrepreneurs' and venture capitalists' exit expectations but can also affect market dynamics and lead to consolidation, possibly hurting VC investment. For example, after an M&A, the newly merged entity may be perceived as larger and more efficient by rivals (Akdoğu 2009; Bernile and Lyandres 2019), thus prompting potential entrants to strategically reposition away from the target's business area or simply shutting down their projects. This competition-reducing effect of startup acquisitions has attracted the attention of competition authorities—including in the US and the EU—particularly insofar as the M&A deals completed by large technology platforms like Google/Alphabet, Amazon, Facebook/Meta, Apple, and Microsoft, collectively known as GAFAM.[2]

[1] https://www.svb.com/startup-outlook-report-2020/

[2] See, for example, the EU's "Digital Markets Act" (enacted on 10/2022), the US House Bill "Platform Competition and Opportunity Act" (introduced 6/2021), or the US DOJ & FTC's new merger guidelines, finalized in 12/2023.

This paper examines the net impact of technology venture acquisitions on venture capital activity within a business area, analyzing how this effect interacts with area characteristics and the type of acquirer. An ideal comparison would entail comparing the change in VC investment in (i) ventures operating in a business area in which an M&A deal is completed, and (ii) ventures operating in a comparable but independent business area. This control business area is intended to provide the counterfactual for the pattern of VC investment that the treated business area would have experienced absent the deal. Such an ideal experiment is challenging to construct in practice.

To address this difficulty, we define the treatment group starting from each of the 2,023 US ventures acquired between 2014 and 2016 as recorded by Crunchbase. For the control group, we begin by considering any US venture that has raised at least one venture capital investment round (Series A or beyond) as of 2014 and is still private and independent as of 2016 ("control focal targets"). To ensure comparability between the two sets of ventures, we match them via propensity score matching (PSM) on several observable characteristics, such as the year in which the venture was founded, the capital raised, and the number of funding rounds raised.

We model the technology sector as a continuous, high-dimensional space where each focal target is one point, and we draw spheres around each of them. We refer to the entire area within a sphere as a "Business/Industry Niche" (BIN) and use it to identify the set of ventures receiving VC funding that operate in the same BIN as the focal target. To construct the BINs, we use ventures' business descriptions and industry keywords in Crunchbase and compute cosine similarities between any focal target-venture pair (Hoberg and Phillips 2010). Ventures that are sufficiently similar to a focal target will be part of the target's BIN. Treated BINs are those whose center is a treated focal target, whereas control BINs are those that center around a control focal target.

By definition, control focal targets were independent ventures as of 2016, but they may belong to a treated BIN when their product is sufficiently similar to that of a treated focal target. We refer to such control targets and the BINs around them as "contaminated." Since the observed VC activity within these contaminated BINs could be driven by the treatment of the focal M&A itself, excluding them from the sample enables us to perform a "clean" comparison between treated and control BINs via a difference-in-differences (DiD) design.

We find that, in net, the signaling effect leads to a tripling in the average amount of VC investment, and an increase in the probability of a new startup raising a VC funding round of almost 7% in the treated BINs. Despite this, we do not find a statistically significant change in the BIN's venture exit rate via M&A or IPO. These results are robust to different empirical designs as well as sample selection procedures.

To better understand the factors that shape investor behavior and expectations, we consider how the signaling effect of venture acquisitions interacts with a BIN's density and M&A-intensity. By BIN density, we refer to the number of ventures that have received VC investment (series A or beyond) in the BIN. By M&A-intensity, we refer to the observed or predicted incident of M&A events in a BIN. We find that the signaling effect is more pronounced in the BINs that have had a greater M&A intensity besides the focal deal, and in the BINs with lower venture density before the focal deal. This indicates that venture acquisitions are just one of many factors influencing investor expectations as far as the future profitability of a BIN, and the positive impact of these acquisitions on investment and entry is particularly strong when they take place in less crowded BINs that are already on the radar of potential acquirers.

Motivated by the ongoing antitrust debate, we also examine the heterogeneous effects of transactions involving GAFAM or a group of prominent acquirers, determined by their number of deals completed within our dataset. These prominent acquirers include telecommunications conglomerates such as Cisco or Verizon, successful startups that had ultimately gone public like Airbnb or Twitter, as well as companies operating primarily outside of the technology sector like Walmart and Johnson & Johnson. We do not find any statistically significant difference associated with the M&A deals involving these large acquirers relative to any other acquirers. However, we find that acquisitions completed by private equity (PE) firms—which have become increasingly prevalent in recent years—have particularly positive effects on VC activity, leading to a large and statistically significant growth in VC investments in their respective BINs. This could be due to PE firms' ability to accurately assess the intrinsic value of a business and strategically time acquisitions based on market and industry cycles, as argued in Nary and Kaul (2023).

Related Literature. To our knowledge, we are among the first to systematically study the net empirical effect of tech acquisitions on venture capital investment in ventures operating in a similar business area, with implications for both entry and innovation.

Phillips and Zhdanov (2023) document a positive correlation between lagged M&A activity and VC investments. Their main variations are different competition laws across countries, and industries are identified via two-digit standard industrial classification (SIC) codes. Instead, we focus on US VC-funded ventures while exploring the variations of nearby M&As: this provides us with a cleaner identification of the effect of venture acquisitions in a certain business area. Eisfeld (2022) uses a structural model to identify how entry-for-buyout and kill zone mechanisms affect startup entry in the enterprise software market, finding that banning venture acquisitions would reduce entry by 8-20%. We analyze a broader set of industries and focus on VC investment, which is potentially more relevant for future innovation and competition (Ewens, Nanda and Rhodes-Kropf 2018; Lerner and Nanda 2020).

The empirical finance literature has typically focused on the relationship between M&A and innovation in the context of public companies, emphasizing how M&As can lead to synergies that help acquirers' innovation efforts (Zhao 2009; Bena and Li 2014) but also reduce the novelty of target's patents (Seru 2014). However, private companies, and in particular technology ventures, represent a key driver of innovation and, in their context, different forces may be at play.[3] A large literature has also investigated the signaling effect of M&As involving public companies focusing on their impact on the market value of firms operating in the same product market (Eckbo 1983; Chatterjee 1986; Song and Walkling 2000) or technological space of the target (Testoni 2022).[4]

We contribute to this literature by studying the signaling effect in private markets, where it may hold greater importance due to the larger information asymmetry among investors and ventures, driven, for example, by lower disclosure requirements. Additionally, the longer investment horizons and the instrumental role these markets play in fostering technological progress further underscore the significance of studying the signaling effect of M&As for VC investment.

Related to our work, another strand of literature has examined the role of acquisitions in generating information spillovers in financial markets (Kimbrough and Louis 2011; Derrien and Kecskés 2013; Li, Lu and Lo 2019; Bernard, Blackburne and Thornock 2020). This occurs because both firms and financial analysts closely monitor these deals, particularly when the acquiring company is large or has garnered significant media attention. Such scrutiny leads to increased attention, enhanced information discovery, and improved dissemination of insights.

By showing the equilibrium response of VC investment to technology venture acquisitions, we also contribute to a burgeoning empirical literature examining the interplay of product market competition and exit opportunities in shaping entrepreneurs'

[3] For example, a recent article by Farida, Fidrmuc and Zhang (2023) studies acquisitions of private targets and finds that they increase the quantity, quality, and value of acquirers' patents. Moreover, the paper argues that, differently from those involving public targets, these deals increase innovation synergies.

[4] Other works have focused on market value spillovers for the rivals of the acquirer (Akdoğu 2009; Cai, Song and Walkling 2011; Gaur, Malhotra and Zhu 2013).

entry and positioning decisions, and venture capitalists' financing strategies (Wang 2018; Warg 2022; Leccese 2023; Li, Liu and Taylor 2023; Pham, Rezaei and Zein 2023; Eldar and Grennan 2024).[5] In particular, differently from us, Wang (2018) focuses on the relationship between exit via M&A and the direction of innovation, finding that entrepreneurs tend to develop innovations that are proximal to potential acquirers' patent portfolios to present themselves as attractive targets, especially when the potential acquirers' market is more concentrated. Warg (2022) finds supportive results but also shows that as the supply of venture capital increases, startups introduce innovations that are more independent of potential acquirers' assets.

Another related issue—yet different from the one analyzed in this article—concerns the development of the target's innovation. On the one hand, Cunningham, Ederer and Ma (2021) show theoretically and empirically in the pharmaceutical industry that the acquirer, to avoid cannibalization of its core product, will "kill" the innovation of the target when it is a close substitute. On the other hand, acquisitions may enable the development of those targets' innovations that would have been impossible due to financial and other constraints (Fumagalli, Motta and Tarantino 2022). More generally, acquisitions may also impact competition within the market and have anti- or pro-competitive effects by enabling the acquirer to eliminate potential competition and reinforce dominance (Gilbert and Newbery 1982; Motta and Peitz 2021) or by facilitating an efficient transfer of inputs and innovation capabilities (Teece 1986; Gans and Stern 2003).[6] Differently from these papers, our focus is on the identification of the overall effect of venture buyouts on nearby ventures' ability to obtain VC investment and grow.[7]

Motivated by the ongoing policy debate, a few empirical studies have also investigated the implications of venture acquisitions performed by GAFAM (Google/Alphabet, Amazon, Facebook/Meta, Apple, and Microsoft). These studies have shed light on the beneficial effects on VC activities within the same market segment (Prado and Bauer 2022), alongside the absence of any reduction in entry by startups (Pan and Song 2023) or other incumbents via M&A (Jin, Leccese and Wagman 2023).[8] Nonetheless, Affeldt and Kesler (2021) provide evidence that such M&A deals may potentially stifle GAFAM

[5]See Rotemberg and Scharfstein (1990), Bolton and Scharfstein (1990), Hellmann and Puri (2000), and O'brien and Salop (2000) for a theoretical treatment of these research streams.

[6]See Bourreau and De Streel (2020) for a comprehensive review of the literature on the effects of startup acquisitions on competition, entry, and innovation.

[7]However, we note that this may not speak directly as to whether a specific M&A is anti- or pro-competitive as far as its relevant market.

[8]Nevertheless, Kamepalli, Rajan and Zingales (2020) provide an empirical example of reductions in VC investment in ventures similar to the target after major acquisitions by Facebook/Meta and Google/Alphabet.

competitors' innovation in the apps market. Thatchenkery and Katila (2023) show that innovation among complementors soared following a reduction in anticompetitive barriers associated with Microsoft, but their profitability dropped. Wen and Zhu (2019) find that after Google's entry threat in a particular market increases, affected developers reduce innovation and raise the prices for the affected apps.[9] Since GAFAM's acquisitions only account for a small fraction of the total number of venture exits via M&A, our study takes a broader perspective to shed light on the relationship between acquisitions and entrepreneurship.[10]

The remainder of the paper is organized as follows. Section 2 presents the theoretical background of our study and develops a few testable hypotheses. Section 3 outlines our empirical strategy and describes our data and sample selection procedure. Section 4 summarizes the baseline results, while the heterogeneous effects by BIN or acquirer attributes are presented in Section 5. Section 6 concludes.

2. Hypothesis Development

A large theoretical literature studies the signaling effects of acquisitions on entry and innovation. A seminal work by Rasmusen (1988) finds that the possibility of a buyout can make entry deterrence strategies suboptimal for a monopolist incumbent, thus inviting entry-for-buyout. This is because potential entrants anticipate that the acquirer will offer a price that has to at least compensate them for the forgone value of independently competing in the market. Phillips and Zhdanov (2013) show that while R&D investment may optimally decrease for large firms as a result of merger activity, it may increase for small firms. This is because large firms may prefer acquiring other companies to access successful innovations rather than investing in R&D themselves. Conversely, small firms have greater incentives to invest in R&D when there is an active market for mergers.

In stock markets, acquisitions of public companies are typically associated with positive abnormal returns to rivals of the target firm (Stillman 1983; Eckbo 1983, 1985; Eckbo and Wier 1985; Mitchell and Mulherin 1996). While coordinated effects that make collusion easier to sustain may explain this empirical pattern, this theory has been rejected in favor of the *Acquisition Probability Hypothesis*, formulated by Song and

[9] Related to the killer acquisition theory, Gautier and Lamesch (2020) examine 175 acquisitions by GAFAM during 2015-2017 and find that a substantial portion of the acquired products and services are no longer supplied, maintained, or upgraded under their original brand names.

[10] Jin, Leccese and Wagman (2023) show that out of the acquisitions of technology firms completed between 2010 and 2020, the acquirer was a GAFAM firm in only 1.42% of the transactions.

Walkling (2000). With supporting evidence, they argue that rivals of initial acquisition targets earn abnormal returns because of the increased probability that they will be targets themselves.

In private markets, if the acquisition of a startup increases the likelihood of acquisitions of other related startups, acquisitions can invite entry-for-buyout and stimulate innovation (Mason and Weeds 2013; Shelegia and Motta 2021; Letina, Schmutzler and Seibel 2024). This signaling mechanism is potentially more relevant in private than in public markets in light of the larger role of information asymmetries between investors and entrepreneurs and the importance of M&A as a successful exit strategy (Ederer and Pellegrino 2023), or as a way to mitigate losses (Mason and Weeds 2013). In short, the literature suggests the following hypothesis:

Hypothesis 1. *A venture buyout may increase VC investment in the business area of the target.*

At the same time, sophisticated VC investors must consider how the market environment may affect a venture's future profitability. Even if the acquisition of a startup signals a more promising market for the focal business area, competition could dissipate most of the future profits if a number of similar ventures are already operating in this market. How ventures in the same BIN differentiate from each other in terms of product design, value proposition, and business model may also affect venture profitability in the future. Since our BIN definition incorporates the similarity of nearby ventures, we anticipate a more positive effect of technology venture buyouts on VC activity in less-dense BINs. Furthermore, the intensity of past and anticipated M&A activity within a BIN can significantly influence investment decisions. On the one hand, BINs with a history of intense M&A activity or where numerous acquisitions are expected may attract substantial attention from both entrepreneurs and investors, thereby amplifying the signaling value of an M&A. On the other hand, investors and entrepreneurs may already have highly positive expectations regarding the prospects of these BINs, which could reduce the marginal value of the signal conveyed by an M&A.

Hypothesis 2. *The positive effect of a venture buyout may be greater in less-dense BINs. Conversely, a higher M&A intensity has an ambiguous effect on the magnitude of the signaling effect.*

Given the critical role of due diligence and potential synergies in driving value creation (Chondrakis 2016), large strategic acquirers with extensive experience in tech M&As are often better equipped to identify promising technology areas. This may both increase the acquirer's returns and also send a stronger signal to entrepreneurs and other investors regarding the profitability and growth prospects of the target's market. As a result, acquisitions completed by large digital platforms, such as GAFAM, or other acquirers with extensive experience in tech M&A may have a larger positive signaling effect than acquisitions completed by other firms.

In contrast, Kamepalli, Rajan and Zingales (2020) show that, in settings with network externalities where customers face switching costs, entry may decrease because the prospect of an acquisition by an incumbent platform reduces the incentives of early adopters to adopt the entrant's product or service. This further decreases prospective payoffs to new entrants, possibly creating a "kill zone." Moreover, classical entry deterrence theories have also emphasized how vertical integration can be pursued to raise rivals' costs (Salop and Scheffman 1983), and how acquisitions could be part of a predatory strategy that discourages nascent competition by signaling the incumbent's efficiency (Saloner 1987) or strategically tying products (Carlton and Waldman 2002).[11] All these theories require the acquirer's dominance combined with behavior aimed at deterring entry,[12] leading to our next hypothesis:

Hypothesis 3. *A venture buyout may increase or decrease VC investment in the business area of the target when the acquirer is a GAFAM firm or a large acquirer.*

It is worth emphasizing that while generally viewed as welfare-enhancing, entry-for-buyout incentives may also lead to inefficiencies by distorting the direction of innovation towards excessive development—relative to the social optimum—of technologies that are complementary (Bryan and Hovenkamp 2020) or incremental (Cabral 2018) to the incumbent's business.

In recent years, the tech industry has experienced a notable shift with the rise of private equity (PE) buyouts of tech ventures (Jin, Leccese and Wagman 2023), which also attracted the attention of industry practitioners.[13] On the one hand, PE firms are relatively new to the tech sector and may lack the same level of expertise and experience as strategic acquirers. These information disadvantages may undermine the signaling value of venture acquisitions involving a PE acquirer. On the other hand, compared to

[11] Denicolo and Polo (2021) argue that the entry-for-buyout incentive dominates in the short-run whereas in the long-run acquisitions may stifle innovation when the incumbent's dominance depends on its past activity levels and thus is reinforced by repeated acquisitions over time.

[12] For example, Shelegia and Motta (2021) show that incumbents can deter entry by simply threatening to imitate an entrant's product.

[13] See, for example, https://www.daimagister.com/resources/private-equity-techs-best-kept-secret/ (accessed 08/01/2024).

other investors, PE firms may be more actively involved in the management of their portfolio firms, focus more on business efficiencies, use more financial leverage, and have a different time horizon in mind. As a result, PE firms might have an advantage in accurately assessing the intrinsic value of a business and in timing their transactions given the market and industry cycles (Nary and Kaul 2023), which has the potential of strengthening the signaling effect.

Hypothesis 4. *The positive effect of a venture buyout may be smaller or greater when the acquirer is a PE firm.*

3. Empirical Strategy and Data

In this section, we first present our empirical strategy and then discuss how we implement it with real data.

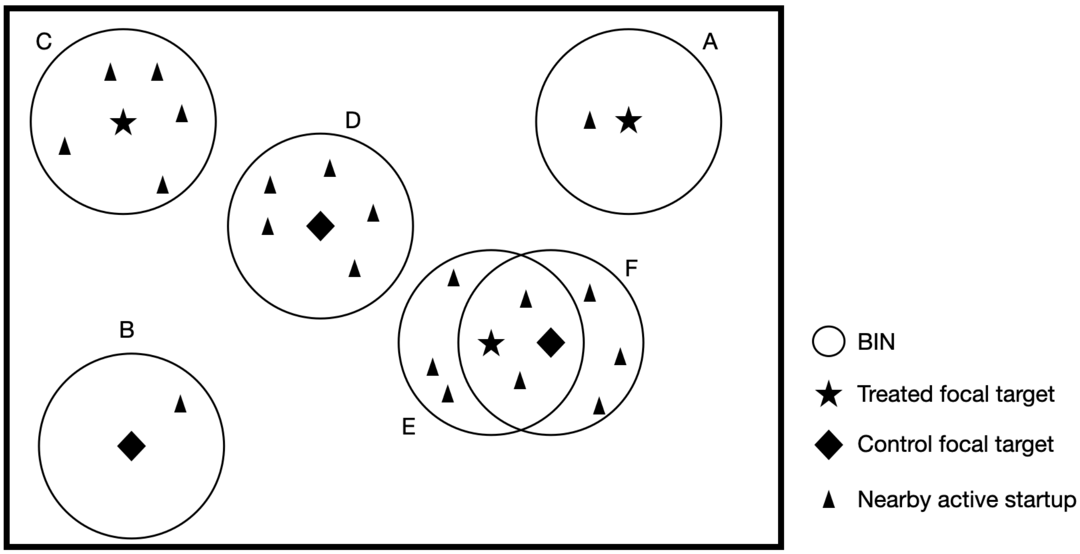
3.1. Empirical Strategy

Ideally, one would want to compare VC activity across two identical but independent business areas, before the acquisition of a venture occurs in one and not in the other. Such an ideal does not exist in practice because business development and technological advances are fluid, and every firm—incumbent or venture entrant—can migrate or extend across business areas and technological directions. As a result, it is difficult to draw a clear and permanent boundary of a market that automatically defines which firm is within.

Our research design focuses on tracking VC investments in the areas near M&A targets. Specifically, we consider the business and technology space as a continuous, high-dimensional space where each venture is one point. As detailed in Section 3.3, each venture acquired between 2014 and 2016 represents a "treated" point in this space, while each venture that is independent as of the end of 2016 is a potential "control" point. We refer to these points as "treated focal targets" and "control focal targets", respectively.

Figure 1 illustrates a two-dimensional screenshot of the space we consider in a certain year. Let us assume that three ventures were acquired in that year, which are represented by the stars (treated focal targets). Diamonds represent control focal targets. These are ventures that were not acquired but are similar in some observable dimensions to the treated focal targets. The circles A, C, E (B, D, F) drawn around treated (con-

FIGURE 1. Research design



trol) focal targets represented the treated (control) BINs.

In our analyses, we exclude contaminated control BINs like F because they are too similar to a treated BIN (E in Figure 1), and hence potentially affected by the treatment itself. After excluding contaminated control BINs, we compare treated BINs (A, C, and E) with clean control BINS (B and D), in dependent variables that capture VC investment and exit activities in these BINs after the focal M&A deals. To the extent that some treated BINs may differ substantially from any clean control BINs in observable pre-treatment attributes, we can test whether treated and control BINs are comparable in pre-treatment trends, and use a more balanced subset of treated and control BINs (such as A and B only) to perform robustness checks.

3.2. Data Source

We use data from Crunchbase, a database that tracks information about technology businesses.[14] Specifically, we focus on all funding and exit activities of US-based ventures from January 2010 to December 2022, including the parameters of venture financing rounds, such as venture information (a unique identifier, name, headquarters country, operating status (closed, acquired, IPO, operating), founding date, and financing dates) and funding information (the size of a funding round in dollars, the date a round

[14] For recent activity in the academic literature that pertains to this database, see for example Lerner et al. (2018), Chatterji et al. (2019), Jia, Jin and Wagman (2021).

was announced, the funding stage such as "Seed," "Series A," "Series B," and the number, names, locations, and types of the participating investors, along with their unique identifiers). The sample comprises 71,275 funding rounds and 36,924 ventures. These rounds represent 32% of all funding rounds recorded in the dataset. We choose to omit earlier rounds—primarily labeled as "seed" (40.89%), "grant" (12.62%), and "pre-seed" (10.31%)—because the dollar amounts in these earlier rounds are often relatively small, and may not reflect a direct response to merger events. These earlier rounds may also be funded by angel and other smaller investors and not driven by VCs. For example, the median amount invested in these earlier rounds is $0.7 million, whereas the same statistic in the rounds we focus on is $7.25 million.

For US ventures that were acquired and/or had an IPO before the end of our sample period, we further collect information on those ventures' exits, including the date of the acquisition or IPO, and, if acquired, the name of the acquirer. We focus on acquisitions that Crunchbase defines as majority-control transactions. Importantly, we also collect a summary of each venture's business as well as a set of keywords assigned to each venture by Crunchbase that are indicative of the venture's business area(s). For example, Crunchbase decribes Uber as a "Mobile app connecting passengers with drivers for hire," attaching the following keywords: "Mobile Apps," "Transportation."

3.3. Sample Selection

We begin by identifying all the US ventures that were acquired between 2014 and 2016. We focus on the years in the middle of our sample period to have sufficiently many years to study before and after the M&As. This sample includes 2,023 acquired tech ventures, to which we refer as "treated focal targets."

For control focal targets, we initially consider all US technology ventures that raised at least one VC investment round as of 2014 and were still private and independent as of the end of 2016. This pool includes 18,362 ventures.

To make control and treated focal targets as comparable as possible, we match them via propensity score matching (PSM) on several characteristics we observe: the year in which the venture was founded, the number of rounds raised, and the logarithm of the funds raised before 2014. This restricts our sample to 1,518 treated focal targets and 10,580 control focal targets. We code each control focal target as "hypothetically" acquired in the same year as their matched treated focal target.[15]

[15]Since we match with replacement and each control focal target may be potentially matched to multiple treated focal targets, we handle these cases by randomly assigning to the control focal target

To define the business area of a focal target, we draw a sphere around it and refer to the area within the sphere as a BIN.[16] In this way, we can track VC activity within BINs over time. A natural question is how to determine the radius of a BIN, which in turn affects the ventures—besides the focal target—that will belong to the BIN. To do so, we use ventures' business descriptions and industry keywords offered by Crunchbase. We define active ventures as those ventures that are not focal targets but have raised venture capital in Series A or beyond up to 2013, and construct word vectors for all active ventures and focal targets. For each active venture-focal target pair in our sample, we then compute a continuous measure of similarity using the cosine similarity method (Hoberg and Phillips 2010). Ventures that are sufficiently similar to a focal target will belong to its BIN. In our main analysis, we set 0.4 as the cosine similarity threshold above which an active venture is part of a BIN. However, we also consider two higher similarity thresholds (0.45 and 0.5) as a robustness check.[17]

In related studies, industries have often been defined via SIC codes (Eckbo 1983; Chatterjee 1986; Phillips and Zhdanov 2023), Value Line industry classification (Mitchell and Mulherin 1996; Song and Walkling 2000), or the text-based network industry classification (Bernile and Lyandres 2019) developed by Hoberg and Phillips (2010).[18] Our approach is related to the latter and we generalize it to the context of private companies by using Crunchbase business descriptions and keywords rather than 10-K filings.[19]

Main sample. Some focal targets have no active ventures in their BIN during 2010-2022, and hence we drop these "inactive" BINs. Panel A in Table 1 presents summary statistics for the 750 treated and 5,232 control focal targets that survive the selection procedure and are part of our main sample. Within control focal targets, we distinguish between "clean" and "contaminated,", where contaminated ones refer to those that lie within the BIN corresponding to at least one treated focal target. Intuitively, the fact that these control focal targets were not acquired may be a consequence of a treated acquisition, and thus the subsequent VC and exit activities within their own BINs can be treated as well. Figure 2 illustrates the distribution of the similarity to the closest treated focal

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one of the M&A years of the treated focal target to which it is matched.

[16]We avoid calling them markets because they may differ from antitrust markets.

[17]A limitation of our approach is that it does not allow us to distinguish between complementarity and substitutability, nor does it enable us to identify vertical relationships.

[18]A different approach is followed by Clougherty and Duso (2009) who focus on a limited sample of 165 large European horizontal acquisitions scrutinized by the European Commission and identifies competitors using the market defined in the corresponding antitrust case.

[19]Similar approaches have been followed by Wang (2018), Warg (2022), Leccese (2023), and Pham, Rezaei and Zein (2023).

target for both treat and control units. The figures indicate that acquisitions tend to cluster together, and contamination affects more than half of the control units.

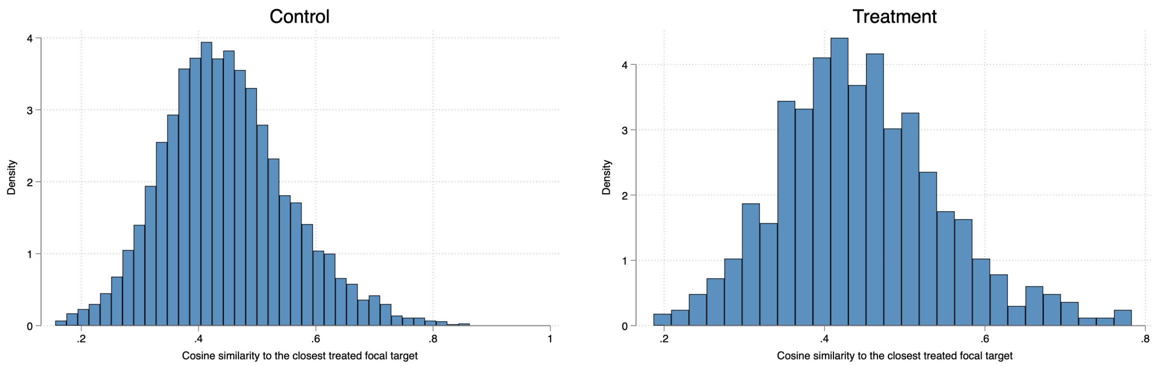

FIGURE 2. Distribution of focal targets' similarity to the closest treated focal target

For each type of focal target, Table 1 provides summary statistics for the year they were founded, the amount, and the number of rounds it raised up until the M&A. We also display measures of the VC activity in the corresponding BIN, and in particular, the total amount of VC invested and the number of rounds raised within the BIN before the M&A. Lastly, we predict for each BIN the probability that a venture is acquired by using a probit regression. The outcome is a binary variable measuring whether any venture is acquired in the BIN between 2010 and 2013 and the covariates include the year in which the focal was founded, the number of rounds and the amount (in logs) it raised, as well as the number of rounds and the capital raised (in logs) by ventures operating in the BIN in the same period.

Panel A of Table 1 shows that while treated focal targets and contaminated controls are relatively similar in all the dimensions considered, the clean control focal targets raised less venture capital, even if older, and exhibit a more moderate VC activity in their BINs. On average, $34.5 million is invested in the ventures within a treated BIN before the focal M&A occurs, and the treated focal target had raised about $23.8 million before exiting via M&A. In comparison, clean control focal targets raise $18.9 million themselves and have about $12.3 million invested in the ventures within their BIN before their hypothetical acquisition. This is consistent with M&A-active areas being more attractive to investors.

Table B.1 in the Appendix reports the same summary statistics but uses narrower BINs defined with higher cosine similarity thresholds. As BINs narrow, it becomes more likely to have BINs with no VC activity throughout the period of study, which in turn reduces the number of focal targets in the final sample. Moreover, narrower BINs imply

Table 1. Summary statistics

	Treated Focal Targets				Clean Controls				Contaminated Controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	N	mean	sd	median	N	mean	sd	median	N	mean	sd	median
Panel A: Main sample												
Focal target year founded	750	2,006.13	4.59	2,007	1,825	2,005.18	4.70	2,006	3,407	2,005.13	4.65	2,006
BIN pre-M&A # of rounds	750	4.05	7.94	2	1,825	1.21	1.87	1	3,407	4.95	8.17	2
BIN pre-M&A VC investment (USD M)	750	34.50	83.57	4	1,825	12.33	65.35	0	3,407	47.34	114.02	6.72
Focal target pre-M&A # of rounds	750	2.45	1.68	2	1,825	2.01	1.43	1	3,407	1.94	1.29	1
Focal target pre-M&A funds (USD M)	750	23.76	36.23	11.50	1,825	18.91	25.74	9.50	3,407	18.03	23.77	9
Predicted M&A probability	746	0.04	0.07	0.02	1,812	0.02	0.02	0.01	3,391	0.04	0.07	0.03
Panel B: Alternative Sample 1												
Focal target year founded	647	2,006.17	4.32	2,007	520	2,006.12	4.36	2,007	891	2,005.99	4.23	2,007
BIN pre-M&A # of rounds	647	3.60	7.01	1	520	1.05	1.80	0	891	3.98	6.88	2
BIN pre-M&A VC investment (USD M)	647	29.17	69.09	3.18	520	8.96	25.69	0	891	30.44	65	5.35
Focal target pre-M&A # of rounds	647	2.41	1.65	2	520	2.07	1.43	2	891	2.05	1.31	2
Focal target pre-M&A funds (USD M)	647	20.22	23.65	11.15	520	18.85	22.62	10	891	19.50	22.08	10.86
Predicted M&A probability	647	0.03	0.06	0.02	520	0.01	0.02	0.01	891	0.03	0.06	0.02
Panel C: Alternative Sample 2												
Focal target year founded	454	2,006.05	4.32	2,006.50	790	2,005.96	4.33	2,006				
BIN pre-M&A # of rounds	454	1.89	3.60	1	790	0.89	1.66	0				
BIN pre-M&A VC investment (USD M)	454	11.85	28.89	0	790	7.02	22.17	0				
Focal target pre-M&A # of rounds	454	2.47	1.70	2	790	2.14	1.52	2				
Focal target pre-M&A funds (USD M)	454	20.65	23.70	11.63	790	19.73	22.72	11				
Predicted M&A probability	454	0.02	0.03	0.01	790	0.01	0.02	0				

Notes: The table displays summary statistics for the key variables characterizing focal targets and BINs.

lower average VC activity within each BIN: for example, Panel B of Table B.1 shows that \$19.2 million is invested in the ventures within the treated BIN before the M&A when we choose a similarity threshold of 0.5, as compared to \$34.5 million under the threshold of 0.4.

Alternative samples. To make treatment and clean controls more similar, we construct two alternative samples for robustness checks. To that end, we run a second PSM, this time matching not only the same focal target's characteristic used before but also the amount of venture capital invested in the BIN before the M&A (in logs) and the predicted M&A probability before 2014. In Alternative Sample 1, we allow treated units to also match contaminated controls, whereas in Alternative Sample 2 we drop contaminated controls before implementing the matching procedure. Figure A.6 summarizes the distribution of the propensity score across merger-years, showing the effectiveness of our additional matching procedure in enhancing covariates balance across groups. The resulting samples are shown in Panel B and C of Table 1, respectively. Unsurprisingly, the treated BINs that survive the procedure display significantly less VC activity, especially in Alternative Sample 2. This is because contaminated controls display more VC activity before the hypothetical focal acquisition. Additionally, focal targets tend to receive less investment before the M&A deal relative to what is shown in Panel A. For example, on average in Alternative Sample 1 (2), the influx of investment in a treated BIN before the focal M&A is about $29 (12) million, which is $5 (23) million lower than the amount invested within an average treated BIN in the main sample. Nonetheless, even after this additional step, a difference in VC activity within the BIN before the M&A still persists.

As shown in Section 4, although it is difficult to match the absolute investment and exit activities between treated and clean control BINs before focal M&A deals, we resort to a battery of econometric tests to ensure the BINs of these two groups follow comparable pretreatment trends.

Dependent variables. We construct several dependent variables measuring activity within treated and control BINs in each year and compare them before and after the acquisition using a DiD design. Table 2 provides the label and definition of each dependent variable considered. For each BIN, we consider the four years before and the six years after the acquisition of the focal target. Figure 1 is a screenshot of a given year, but in practice, acquisitions can take place in 2014, 2015, and 2016.

TABLE 2. Dependent variables measuring VC and exit activity

Variable label	Definition
VC investment	Logarithm of the total amount of VC invested (in USD) in the BIN in a given year + 1
1{Entry}	Dummy equal to one if a new venture raises VC round in the BIN in a given year
1{Exit}	Dummy equal to one if a venture in the BIN exits via IPO or M&A in a given year
Rounds	Count of the total number of VC rounds (Series A or beyond) raised in the BIN in a given year

Empirical Specifications. In our main specification, we consider the four years before and the six years after each real and hypothetical focal M&A and implement the following standard two-way fixed effects (TWFE) DiD design:

$$y_{it} = \alpha_i + \alpha_t + \beta \cdot (Treat_i \times Post_t) + \gamma \cdot (\mathbf{Z}_i \times Post_t) + \varepsilon_{it}, \tag{1}$$

where i is a focal target (or equivalently a BIN, given that each focal target uniquely identifies its BIN) and $t \in \{-4, -3, \ldots, 0, \ldots, 6\}$ represents the years to the focal deal, so that $t = 0$ when the year equals the year of the focal M&A. Additionally, y is one of the dependent variables in Table 2, *Treat* is a binary variable equal to one if the focal target is treated, *Post* is a binary variable equal to one when $t > 0$, and α_i and α_t are BIN and time fixed effects. Note that *Post* can be equal to one for a control BIN as well because we assume the timing of the hypothetical M&A for the center of the control BIN is the same as the actual acquisition time of the focal target of the treated BIN to which it matches. This way, the coefficient of *Post* alone captures general industry trends applicable to both treated and control BINs, while the coefficient of *Treat* $\times$ *Post* captures the DiD effect of the focal M&A. The vector $\mathbf{Z}$ comprises covariates, including the year in which the focal target was founded, the VC investment raised by the focal target and in total by other ventures within the BIN before the actual or hypothetical deal, and the predicted probability of an M&A in the BIN before 2014. Standard errors are clustered at the BIN level.

Our preferred specification includes the interaction term $Z_i \times Post_t$, although we will also consider regressions without it. The reason for this choice is that treated and clean control BINs differ in the absolute magnitude of certain pre-treatment observables. We want to account for the possibility that BINs may differ before and after the onset of both real and hypothetical M&As due to varying market development trends, rather than solely because of the focal M&A deal. For example, BINs that have attracted billions in VC investment may follow a rather different development path from BINs that have attracted considerably smaller amounts, even without the focal M&A deal.

The empirical strategy outlined above relies on the assumption that VC activity follows similar trends across both treated and control units before the focal M&A. This allows the control units to serve as a counterfactual for what would have occurred in the absence of the deal. To test the validity of this assumption, we must ensure that the parallel-trends assumption holds. To do so, we conduct an event study to determine whether statistically significant differences exist in the outcomes between the groups during each period before the focal M&A (i.e., before period 0). Furthermore, this analysis also enables us to shed light on the dynamic effect of venture acquisitions. As a robustness check, we run the event study and the DiD design for both the main sample and the two alternative samples.

Recent research in econometrics has shown that when the treatment is staggered as in our setting, a standard two-way fixed effects (TWFE) DiD design has the potential to yield biased estimates (see Baker, Larcker and Wang (2022) and Roth et al. (2023) for a review of the literature). To address this concern, we also use our main and alternative samples to implement the Doubly-Robust estimation procedure for staggered treatments, as proposed by Callaway and Sant'Anna (2021). This approach identifies the average treatment effect on the treated (ATT) in a year t for the *cohort* of treated BINs where the acquisition occurred in year g by comparing their expected change in outcome between years $g+1$ and t to that of control BINs which we *assume* are acquired in year g. Then, we also average the cohort-year ATT at different lengths of exposure to the treatment to summarize our results in event-study plots.

As indicated earlier in this section, our setting is potentially characterized by covariate-specific trends in VC activity over time and by varying distribution of covariates across groups. This implies that a conditional parallel trends assumption becomes more plausible than an unconditional parallel trends assumption. Since the framework developed by Callaway and Sant'Anna (2021) allows for the parallel trends assumption to hold after conditioning on covariates, our preferred specification uses the covariates in Z_i for propensity score matching between treated and control units, although we will also consider regressions where we do not include any covariate. The advantage of using the Doubly Robust estimation is that it can ensure an unbiased estimation of ATT if either the conditional parallel trend assumption is satisfied or the propensity score model is correctly specified.

4. Baseline Results

Table 3 summarizes our baseline results using the main sample and standard DiD regression as described by Equation 1. The odd-numbered columns present the results without controlling for $Z \times Post$. The even-numbered columns include such controls on the right-hand side.

With and without these controls, we find that venture acquisitions lead to a large and statistically significant increase in VC activity (at the 95% confidence level). According to Column (2), venture capital invested is estimated to be about 3.12 times higher after the acquisition of a focal target, which corresponds to about $16.23 million more invested in other ventures in the corresponding treated BIN each year.[20] Additionally, the probability of a new venture raising a VC round increases by almost 7% (Column 4). Despite this, we do not find any statistically significant increase in the probability of a venture being acquired or having an IPO (Column 6). The coefficients on the interaction of $Z_i \times \ post_t$ suggest that, after the acquisition, VC activity tends to be lower in those BINs that were more active before the deal or had a higher expected probability of acquisition. To be conservative, we do not attribute these changes to the focal M&A transaction and only interpret the coefficient of $Treatment_i \times \ post_t$ as the main effect of the focal M&A deal.

TABLE 3. Average effect of M&A: Generalized DiD

VARIABLES	(1) VC investment	(2) VC investment	(3) 1{Entry}	(4) 1{Entry}	(5) 1{Exit}	(6) 1{Exit}	(7) Rounds	(8) Rounds
Treatment × Post	1.395***	1.415***	0.0514***	0.0686***	0.00175	0.00305	0.00487	0.375***
	(0.218)	(0.229)	(0.0137)	(0.0147)	(0.00275)	(0.00269)	(0.0517)	(0.0590)
Focal target year founded × Post		-0.0134		8.28e-05		-0.000114		0.000233
		(0.0211)		(0.00138)		(0.000264)		(0.00604)
Focal target value × Post		-0.179***		-0.00963**		0.000717		-0.0257
		(0.0694)		(0.00454)		(0.000811)		(0.0199)
BIN investment pre-M&A × Post		0.0170		-0.000950		0.000110		-0.0867***
		(0.0134)		(0.000856)		(0.000255)		(0.00537)
Predicted M&A probability × Post		-0.730		-0.499***		-0.0747		-0.00470
		(1.707)		(0.0992)		(0.107)		(0.134)
Observations	25,750	25,580	25,750	25,580	25,750	25,580	23,000	22,840
R-squared	0.392	0.393	0.354	0.356	0.128	0.129		
BIN FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Poisson							✓	✓
Mean	5.843	5.843	0.410	0.410	0.0167	0.0167	1.075	1.075

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table displays our baseline results obtained from estimating the TWFE model in Equation 1 in the main sample, excluding contaminated controls. The odd-numbered columns present the results without controlling for $Z \times Post$. The even-numbered columns include such controls on the right-hand side. Robust standard errors in parentheses are clustered at the focal target level.

Since the number of rounds is a count variable, we estimate a Poisson regression model. Columns (7) and (8) display the results with and without adding $Z \times Post$ to the regression. When conditioning on these covariates, we find that the number of rounds raised within a BIN is 45.5% higher after a focal venture is acquired.[21]

To shed light on the dynamic effect of acquisitions, we consider event-study regressions on the main sample, including $Z_i \times Post_t$ in the specification. Figure 3 shows that

[20] Because the dependent variable is logged, the effect of *Treatment* going from 0 to 1 is calculated as $exp(\text{coefficient of } Treatment \times Post) - 1$.

[21] In a Possion regression, the marginal effect of *Treatment* going from 0 to 1 is $exp(\text{coefficient of } Treatment \times Post) - 1$.

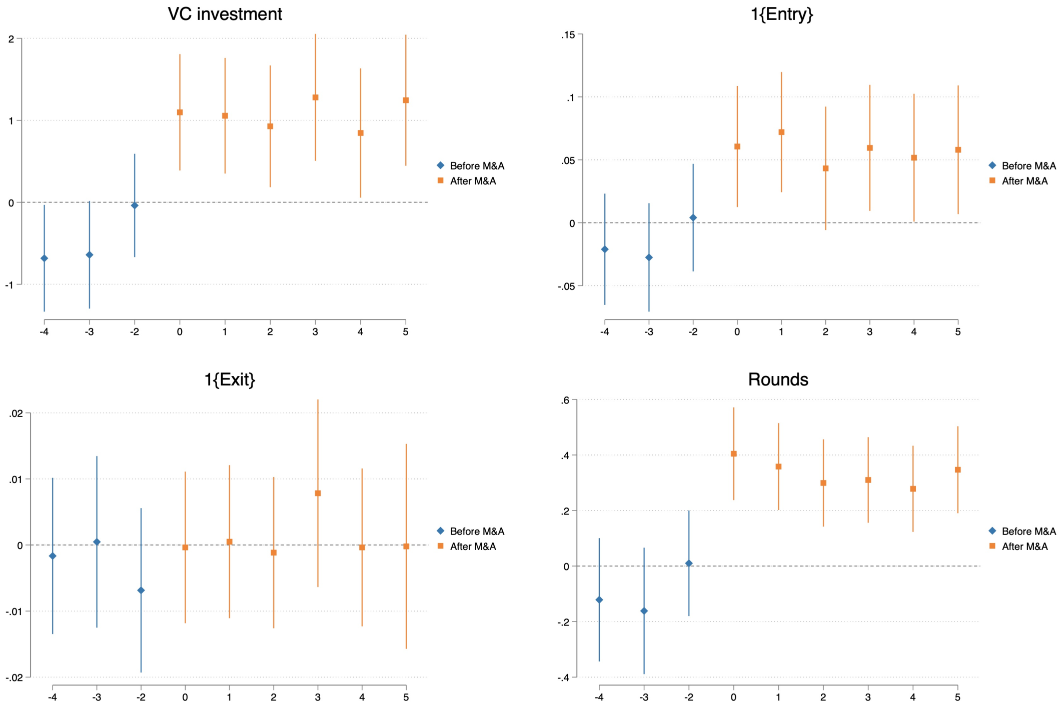

FIGURE 3. Event-study for the effect of M&A

Notes: The plots refer to our preferred specification which is the one estimated in the main sample and in which we include $Z_i \times Post_t$. The confidence intervals shown are at the 95% level. Contaminated controls are excluded from the regression.

the estimated effects are particularly pronounced during the year of the deal and in the subsequent year for our entry measure, as well as for the number of rounds. In contrast, the effect appears to be more homogeneous across years for VC investment. This approach also allows us to provide evidence supporting the validity of the parallel-trend assumption in our setting.[22]

Overall, our results provide support in favor of Hypothesis #1 as they are consistent with the existence of a positive signaling effect that boosts VC investment and stimulates the entry of new ventures seeking external funding to scale their operations. However, this signaling effect does not seem to increase exit rates. This could be attributed to the fact that BINs attracting VC investors tend to reach saturation rapidly.

Robustness checks. We run several robustness checks. First, we perform the same analyses using the alternative samples described in Section 3.2. This entails excluding some

[22]Figure 3 shows a potential violation in VC investment trends four years before the treatment. However, this deviation occurs relatively far from the treatment period and is absent in all alternative specifications, which consistently yield robust estimates of the ATT. These factors support the validity of our findings.

of the treated BINs characterized by more intense VC activity before the acquisition. Table 4 shows that our main results are robust. Moreover, Figure A.1 in the Appendix illustrates how the parallel trends assumption is satisfied even in this sample, with dynamic effects similar to those in Figure 3.

TABLE 4. Average effect of M&A: Generalized DiD after PSM

VARIABLES	(1) VC investment	(2) VC investment	(3) 1{Entry}	(4) 1{Entry}	(5) 1{Exit}	(6) 1{Exit}	(7) Rounds	(8) Rounds
Panel A: Main sample								
Treatment × Post	1.395***	1.415***	0.0514***	0.0686***	0.00175	0.00305	0.00487	0.375***
	(0.218)	(0.229)	(0.0137)	(0.0147)	(0.00275)	(0.00269)	(0.0517)	(0.0590)
Observations	25,750	25,580	25,750	25,580	25,750	25,580	23,000	22,840
R-squared	0.392	0.393	0.354	0.356	0.128	0.129		
Panel B: Alternative Sample 1								
Treatment × Post	1.421***	1.258***	0.0631***	0.0725***	0.00368	0.00198	-0.0109	0.341***
	(0.275)	(0.284)	(0.0174)	(0.0183)	(0.00329)	(0.00322)	(0.0860)	(0.0982)
Observations	11,670	11,670	11,670	11,670	11,670	11,670	10,500	10,500
R-squared	0.439	0.439	0.397	0.398	0.124	0.125		
Panel C: Alternative Sample 2								
Treatment × Post	1.313***	1.147***	0.0665***	0.0677***	0.00613**	0.00519*	0.0526	0.345***
	(0.263)	(0.267)	(0.0172)	(0.0177)	(0.00283)	(0.00289)	(0.0934)	(0.106)
Observations	12,440	12,440	12,440	12,440	12,440	12,440	10,740	10,740
R-squared	0.372	0.373	0.341	0.341	0.108	0.109		
BIN FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
$Z_i \times Post$	NO	YES	NO	YES	NO	YES	NO	YES
Poisson							✓	✓
Mean	5.402	5.402	0.381	0.381	0.0139	0.0139	0.952	0.952

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table displays the results obtained from estimating the TWFE model in Equation 1 comparing the main sample (Panel A), the alternative sample 1 (Panel B), and alternative sample 2 (Panel C). Contaminated controls are excluded in all regressions. All panels refer to the preferred specification where $Z \times Post$ is included. Robust standard errors in parentheses are clustered at the focal target level.

Second, we consider the main sample in the whole sample period—rather than only the four years before and the six years after the acquisition—and use the method developed in Callaway and Sant'Anna (2021) to identify the average treatment effect on the treated (ATT) in year t for each cohort of BINs whose focal target was acquired in year g, with $g = \{2014, 2015, 2016\}$.

Table 5 reports the weighted average of all cohort-year average treatment effects with weights proportional to the cohort size. Panel A reports the estimates of the ATT for the main sample, whereas Panels B and C refer to the two alternative samples. When we match on covariates, Column 3 shows results similar to those in Table 3. Additionally, Figures A.3 and A.4 in the Appendix display the dynamic effects estimated using the approach in Callaway and Sant'Anna (2021) for both alternative samples.

TABLE 5. Average effect of M&A across samples using staggered DiD

DEP. VAR.	(1) ATT	(2) SE	(3) ATT	(4) SE	(5) Mean
Panel A: Main sample					
VC investment	0.958***	0.257	1.547***	0.305	6.062
1{Entry}	0.033*	0.017	0.075***	0.019	0.416
Rounds	0.513***	0.065	0.473***	0.072	1.126
1{Exit}	0.004	0.004	-0.003	0.008	0.017
Observations	33,254		33,254		
Panel B: Alternative Sample 1					
VC investment	0.876***	0.298	1.342***	0.432	5.649
1{Entry}	0.043**	0.020	0.079***	0.027	0.390
Rounds	0.486***	0.069	0.517***	0.098	0.997
1{Exit}	0.009**	0.004	0.002	0.006	0.015
Observations	15,171		15,171		
Panel C: Alternative Sample 2					
VC investment	0.919***	0.303	1.333***	0.314	3.637
1{Entry}	0.054**	0.021	0.087***	0.022	0.268
Rounds	0.304***	0.059	0.334***	0.063	0.477
1{IPO or M&A}	0.010**	0.004	0.007	0.004	0.007
Observations	16,172		16,172		
Match on covariates			✓		

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table displays the results obtained from the staggered DiD model comparing the main sample (Panel A), the alternative sample 1 (Panel B), and alternative sample 2 (Panel C). Contaminated controls are excluded in all regressions. Column 1 shows the ATT without controlling for $Z \times Post$, whereas column 3 includes such controls on the right-hand side. The respective robust standard errors are reported in even-numbered columns and clustered at the focal target level.

Using a cosine similarity threshold of 0.4—as we do in our previous analyses—yields, on average, 29 active ventures similar to each focal target throughout our entire sample from 2010 to 2022. Since one can argue that such a BIN definition might be too wide and not allow us to effectively capture venture competition, we test the robustness of our findings to narrower BIN definitions. Specifically, we use 0.45 and 0.50 as the thresholds for the cosine similarity of an active venture to a focal target required for the two to belong to the same BIN. When we use a threshold of 0.45 (0.5) the average number of active ventures similar to a focal target decreases to about 21.05 (15.66). As shown in Appendix B, our analyses confirm the robustness of the estimated ATTs to different BIN definitions in the main and alternative samples, for both the empirical designs described in Section 3.

5. Heterogeneous Effects by BIN and Acquirer Attributes

This section explores the heterogeneous effects of venture acquisitions as a function of BIN and acquirer attributes.

Heterogeneous effects by BIN attributes. We begin by examining two BIN attributes: BIN density and BIN M&A intensity.

As described in Hypothesis #2, rational investors shall anticipate the future profitability of a venture to depend on the extent to which it competes head-to-head with other ventures in the same BIN, how it relates to or complements ventures in nearby BINs, and how it differentiates from similar or nearby ventures. We are not aware of any clear, comprehensive product description for all VC-funded ventures. Even if such a description exists, ventures may change their product and technology focus areas at any time within and across funding rounds. This implies that we cannot characterize ventures as substitutes or complements, nor can we define the relationships between ventures as horizontal competitors or vertical partners.

That being said, we follow Hoberg and Phillips (2010) in defining pair-wise similarity between ventures, based on their business descriptions and keywords in Crunchbase. In particular, we construct two variables to describe the density of ventures in a BIN: (i) Simple-BIN-density, which measures the total number of active ventures within a BIN right before the actual or hypothetical merger; (ii) Weighted-BIN-density which is similar to the Simple-BIN-density but weighs each active venture within the BIN by its cosine similarity to the focal target. Both measures attempt to capture the 'crowdedness' of a BIN before the actual or hypothetical treatment of M&A. On average, there are 2.75 active ventures in treated BINs and 2.46 in control BINs.[23] If we restrict attention to

[23]Note that these numbers refer to the number of active ventures within a BIN *in a single year* up until the actual or hypothetical M&A, whereas the number of active ventures within a BIN that we report at the end of Section 4 is the total throughout the entire sample period of 2010-2022.

clean controls, the average number of active ventures becomes 0.84. Weighting active ventures by their similarity to the focal target leads to an average Weighted-BIN-density of 1.30 (1.16) in treated (control) BINs.

For what concerns a BIN's M&A-intensity, we use two binary variables. The first is the predicted probability of the focal target (treated or control) being acquired based on target and BIN information right before the (real or hypothetical) treatment, as defined in Section 3.2. Table 1 shows that, in the Main sample, the average predicted probability of an M&A is 4% for treated and control BINs, whereas it is 2% for clean controls. For ease of interpretation, we define a dummy of "High predicted-M&A-intensity" to be one if the predicted M&A likelihood is above the median, and zero otherwise. By construction, half of the sample has a high predicted intensity. The second variable, which we call "High past-M&A-intensity," is a dummy equal to one when at least one acquisition took place within the BIN before the focal deal since 2010. In our main sample, this is the case in about 3.5% of the BINs, with the statistic being slightly higher (3.7%) for treated BINs, and lower (3.4%) for control BINs.

Next, for each dependent variable, we estimate three separate regressions of the following form:

$$\begin{aligned} y_{it} = & \alpha_i + \alpha_t + \beta \cdot \left(Treat_i \times Post_t\right) + \delta \cdot \left(Treat_i \times Post_t \times H_i\right) + \\ & + \xi \cdot \left(Post_t \times H_i\right) + \gamma \cdot \left(\mathbf{Z}_i \times Post_t\right) + \varepsilon_{it}, \end{aligned} \tag{2}$$

where the variables are defined as in Equation 1 and H_i is Simple-BIN-density, Weighted-BIN-density, High predicted-M&A-intensity, or High past-M&A-intensity.

Table 6 summarizes our results. Panel A shows that the signaling effect—and in particular the total amount invested—tends to be undermined by the density of the BIN. This is in line with the conjecture in Hypothesis #2. Specifically, we find that, while still positive, the net effect of venture acquisitions is 27.39% lower when an additional venture is active in the BIN before the deal. Panel B indicates that the size of this signaling-reducing effect of BIN density is greater when the nearby surroundings of the focal target become denser. This could be driven by the fact that denser BINs are characterized by more intense venture competition. Additionally, a higher density could reduce the significance of updates about the market's potential, as other ventures are already active and have signaled profitability. Finally, a higher density could lead investors to believe that the optimal time to invest in the market has already passed.

Panels C and D of Table 6 show that the signaling effect on VC investment and entry increases with both past and predicted BIN M&A-intensity, although δ is not statistically

TABLE 6. Heterogeneous effects of M&A across different BINs

VARIABLES	(1) VC investment	(2) 1{Entry}	(3) 1{Exit}	(4) Rounds
Panel A: Simple density				
Treatment × Post	1.579***	0.0680***	0.00370	0.352***
	(0.248)	(0.0155)	(0.00374)	(0.0798)
Simple-density × Treatment × Post	-0.320**	-0.000375	-0.00137	-0.00685
	(0.126)	(0.00647)	(0.00307)	(0.0169)
Simple-density × Post	0.440***	-0.00446	0.00123	0.0122
	(0.131)	(0.00684)	(0.00308)	(0.0171)
R-squared	0.393	0.355	0.129	
Panel B: Weighted density				
Treatment × Post	1.595***	0.0681***	0.00381	0.352***
	(0.247)	(0.0155)	(0.00374)	(0.0786)
Weighted-density × Treatment × Post	-0.717***	-0.00111	-0.00271	-0.0144
	(0.272)	(0.0140)	(0.00664)	(0.0359)
Weighted-density × Post	0.946***	-0.00885	0.00199	0.0254
R-squared	0.393	0.355	0.129	
Panel C: Predicted M&A intensity				
Treatment × Post	0.965***	0.0581***	0.00294	0.405***
	(0.245)	(0.0166)	(0.00195)	(0.143)
High predicted-intensity × Treatment × Post	0.886*	0.00722	-0.00144	-0.0310
	(0.454)	(0.0288)	(0.00568)	(0.152)
High predicted-intensity × Post	-0.261	-0.00978	-0.00635*	-0.221**
	(0.412)	(0.0264)	(0.00345)	(0.106)
R-squared	0.393	0.355	0.129	
Panel D: Past M&A intensity				
Treatment × Post	1.313***	0.0576***	0.00292	0.344***
	(0.227)	(0.0145)	(0.00239)	(0.0595)
High past-intensity × Treatment × Post	3.382**	0.219***	0.0543	0.323*
	(1.370)	(0.0795)	(0.0444)	(0.166)
High past-intensity × Post	-2.528**	-0.219***	-0.162***	-0.248*
	(1.141)	(0.0589)	(0.0332)	(0.146)
R-squared	0.393	0.355	0.138	
Observations	25,750	25,750	25,750	23,000
BIN FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table displays the results obtained from estimating Equation 2 in the main sample, excluding contaminated controls. In Panel A H_i is Simple-BIN-density, in Panel B H_i is Weighted-BIN-density, in Panel C H_i is High predicted-M&A-intensity, and in Panel D H_i is High past-M&A-intensity. All panels refer to the preferred specification where $Z \times Post$ is included. Robust standard errors in parentheses are clustered at the focal target level.

significant when the outcome is entry and H_i=High predicted-intensity. This sheds light on the forces highlighted in Hypothesis #2, indicating that an additional acquisition in a BIN with already high M&A intensity amplifies the magnitude of the positive signaling effect, more so than offsetting the potentially negative effect generated by the already high expectations regarding the prospects of these BINs. Furthermore, the negative estimate of ξ in Panel D suggests that BINs with high M&A activity before the focal actual or hypothetical acquisition tend to experience a slowdown in VC activity afterward. This pattern aligns with standard market dynamics, where initial intense M&A activity generates enthusiasm among investors and entrepreneurs who rush to capitalize on emerging opportunities. However, as these opportunities are increasingly exploited, the market begins to stabilize, and VC activity diminishes. We find that in these contexts a new acquisition can revitalize the BIN, attracting renewed venture capital activity.

Heterogeneous effects by acquirer attributes. We begin by considering (i) GAFAM and (ii) other top strategic acquirers excluding GAFAM. The latter group is defined as the companies in the top 10 percentile in terms of acquisitions completed after 2010 in our data. We choose to also include acquisitions performed after 2016 to define top acquirers because we want to capture the companies that, even if not yet top acquirers at the time of acquisition, were growing, which is something that investors and entrepreneurs could anticipate and react accordingly. Our group of top acquirers includes large well-known digital companies such as Adobe, Oracle, or Salesforce, as well as telecommunication conglomerates (e.g., WPP, Cisco, Verizon), software conglomerates (Constellation Software), successful ventures that had gone public (e.g., Airbnb, Snap, Spotify, Twitter) and also companies whose primary business lies outside of the technology space such as Walmart, Unilever, Johnson & Johnson, and Merck.

On the one hand, deals completed by GAFAM or other top acquirers could provide a stronger signal of market profitability as the expertise of these acquirers may enable them to identify emerging trends and areas of high potential. On the other hand, these deals may raise competition concerns if these acquirers hold a dominant position. Additionally, given the growing importance of PE buyouts in the tech space, we separately consider the implications of such acquisitions.

Econometrically, we construct three binary variables that equal one when the acquisition is completed by a PE firm, GAFAM, or a top acquirer that is not PE nor GAFAM. We call these variables PE_i, $GAFAM_i$, and TOP_i, respectively. Overall, our Main sample comprises 54 distinct PE acquirers and 60 top acquirers, in addition to the 5 GAFAM firms. Collectively, these groups are responsible for 206 out of the 750 focal acquisitions in our Main sample, with GAFAM firms accounting for 27 of these deals and PE firms contributing to 59.

Then, for each dependent variable, we estimate three separate regressions of the following form:

$$\begin{aligned} y_{it} =& \alpha_i + \alpha_t + \beta \cdot \left(Treat_i \times Post_t\right) + \delta \cdot \left(Treat_i \times Post_t \times Acquirer_i\right) + \\ &+ \gamma \cdot \left(\mathbf{Z}_i \times Post_t\right) + \varepsilon_{it}, \end{aligned} \tag{3}$$

where the variables are defined as in Equation 1 and $Acquirer_i = \{PE_i, GAFAM_i, TOP_i\}$, depending on the regression. As before, standard errors are clustered at the BIN level.[24]

Next, we consider Hypotheses #3 and #4. Table 7 shows that PE buyouts of ventures provide a stronger signaling effect. This could be explained by PE firms' comparative advantage in evaluating market potential and timing their transactions, which may strengthen the signaling effect. In contrast, venture acquisitions completed by GAFAM or other top acquirers do not display any differential effect.[25] This contrasts the recent concerns raised by competition authorities, suggesting that, even if the negative competition effects that have been highlighted by the authorities exist, they may be more than offset by the positive signal conveyed to the market and subsequent investment and entry.

Lastly, we explore how an acquirer's proximity to the target in the business space impacts the signaling effect. On the one hand, greater proximity could discourage VC activity if the acquisition increases concentration and makes the merged entity more efficient. On the other hand, acquirers operating in a closer business area may have greater expertise, and hence their acquisition could convey a stronger signal about market profitability. We construct the variable "Overlap" by computing the cosine similarity between the business descriptions of the acquirer and target and replace $Acquirer_i$ with this measure in Equation 3. Panel D of Table 7 shows that δ is not statistically significant for three out of our four dependent variables. However, for the last dependent variable, when the acquirer's business is more similar to that of the target, it is possible that the *expertise*-driven force dominates the *concentration*-driven one and the signaling effect becomes stronger, thus prompting an increase in the number of VC rounds in the target's BIN.

[24]Note that the specification does not include the term $Acquirer_i \times Post_t$ because acquirer dummies are zero for all control BINs.

[25]We also perform the same analysis for public versus private non-PE acquirers and obtain similar results.

TABLE 7. Heterogeneous effects of M&A across different acquirers

VARIABLES	(1) VC investment	(2) 1{Entry}	(3) 1{Exit}	(4) Rounds
Panel A: PE firm				
Treatment × Post	1.275***	0.0518***	0.00275	0.360***
	(0.232)	(0.0148)	(0.00292)	(0.0565)
PE acquirer × Treatment × Post	1.286**	0.112***	-0.00875	0.230
	(0.638)	(0.0396)	(0.00601)	(0.180)
R-squared	0.393	0.355	0.129	
Panel B: Any GAFAM firm				
Treatment × Post	1.389***	0.0595***	0.00242	0.372***
	(0.225)	(0.0144)	(0.00280)	(0.0564)
GAFAM × Treatment × Post	-0.142	0.0530	-0.0125	0.00753
	(1.255)	(0.0708)	(0.00942)	(0.157)
R-squared	0.392	0.355	0.129	
Panel C: Top except GAFAM and PE firms				
Treatment × Post	1.318***	0.0608***	0.00312	0.372***
	(0.241)	(0.0153)	(0.00300)	(0.0570)
Top acquirer × Treatment × Post	0.413	0.00288	-0.00698	0.00223
	(0.508)	(0.0320)	(0.00633)	(0.0950)
	(0.508)	(0.0319)	(0.00617)	(0.0945)
R-squared	0.392	0.355	0.129	
Panel D: Acquirer-Target Overlap				
Treatment × Post	1.306***	0.0483**	0.00211	0.287***
	(0.327)	(0.0206)	(0.00379)	(0.0686)
Overlap × Treatment × Post	0.467	0.0776	-0.000601	0.472**
	(1.429)	(0.0864)	(0.0161)	(0.196)
R-squared	0.392	0.355	0.129	
Observations	25,750	25,750	25,750	23,000
BIN FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table displays the results obtained from estimating Equation 3 in the main sample, excluding contaminated controls. In Panel A $Acquirer_i$ is one when the acquirer is a PE firm, in Panel B $Acquirer_i$ is one when the acquirer is a GAFAM firm, in Panel C $Acquirer_i$ is one when the acquirer is a top acquirer, and in Panel D $Acquirer_i$ is our measure of Acquirer-Target overlap. All panels refer to the preferred specification where $Z \times Post$ is included. Robust standard errors in parentheses are clustered at the focal target level.

6. Conclusion

We investigate the effect of technology venture acquisitions on investment in the business area of the target. Utilizing data from Crunchbase on acquisitions and venture capital rounds in the United States, we analyze technology ventures that were acquired between 2014 and 2016 along with a group of control ventures that remained independent as of 2016. By modeling the technology sector as a continuous, high-dimensional space where each venture is represented as a point, we apply textual analysis to track investments in ventures operating in similar business areas.

Using a difference-in-differences approach, we find that venture acquisitions boost investment and new venture entry, which aligns with the idea that venture acquisitions signal the size and potential of the target's business area. This effect is driven by business areas with a lower density of ventures before the deal and with a greater predicted or past M&A intensity.

The acquisition of technology ventures by large incumbents, especially leading technology platforms, has been at the forefront of recent antitrust debates. We help inform the debates by showing that the positive signaling effect of M&As is not weaker when the deal is completed by GAFAM or other top acquirers.

It is worth noting that our findings do not speak directly as to whether technology venture acquisitions promote or harm market competition, because investor interest in ventures near a focal target is driven, e.g., by the expected profitability of the ventures rather than consumer or social welfare. A business area could be more profitable in the future because consumer demand is strong and ventures find new or efficient ways to address it, or because one anticipates lessened market competition and thus supracompetitive profits.

For the same reason, our findings do not speak to the nature of innovation in the business areas that attract more investment after the acquisition of the focal target. VC-backed technology ventures play a crucial role in promoting innovation and are increasingly choosing to exit through acquisitions. While acquisitions can encourage investment and new venture entry by signaling the profitability of the business area and providing opportunities for technology buyouts, they may also hinder and distort innovation if entrepreneurs are deterred by the prospect of competing with strong, established incumbents. This is particularly relevant in light of the M&A activities of large corporations like GAFAM. Identifying the effect of venture acquisitions on market competition and innovation is an important direction for future research.

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Appendix A. Additional Robustness Analyses: Alternative Sample and Empirical Strategy

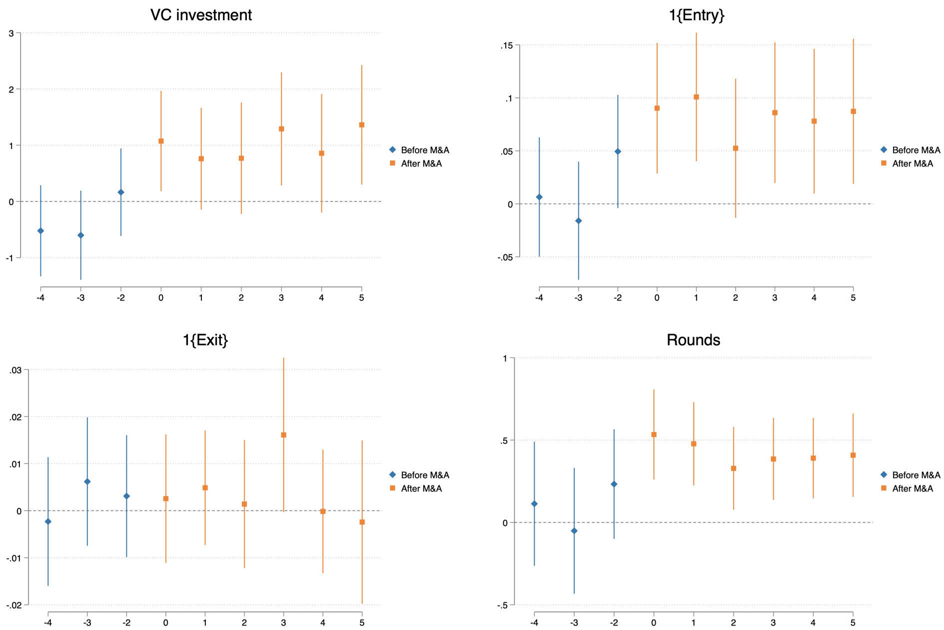


FIGURE A.1. Event-study in Alternative Sample 1

Notes: The plots refer to our preferred specification which is the one wherein we include $Z_i \times Post_t$. The confidence intervals shown are at the 95% level. Contaminated controls are excluded from the regression.

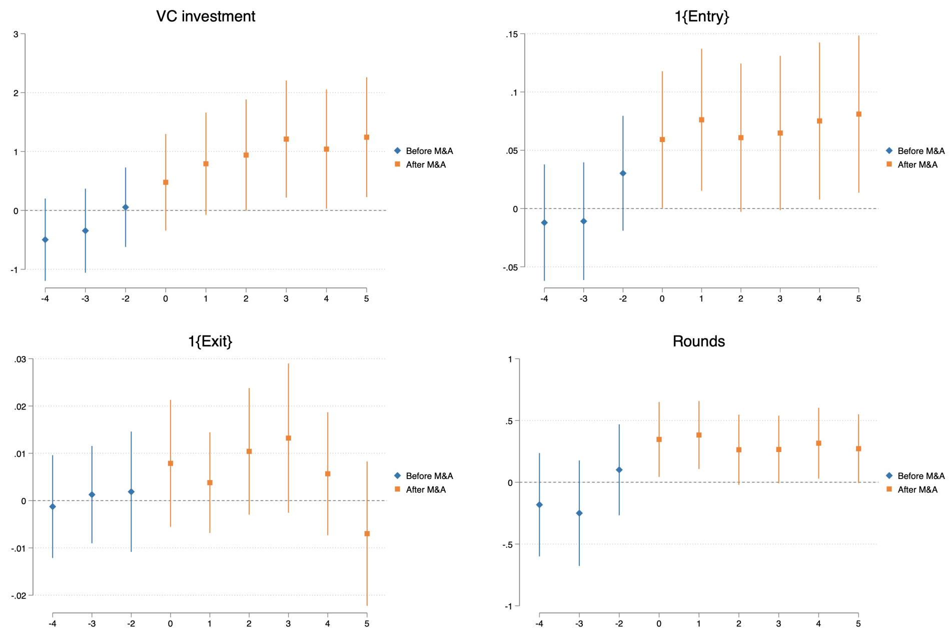


FIGURE A.2. Event-study in Alternative Sample 2

Notes: The plots refer to our preferred specification which is the one wherein we include $Z_i \times Post_t$. The confidence intervals shown are at the 95% level. Contaminated controls are excluded from the regression.

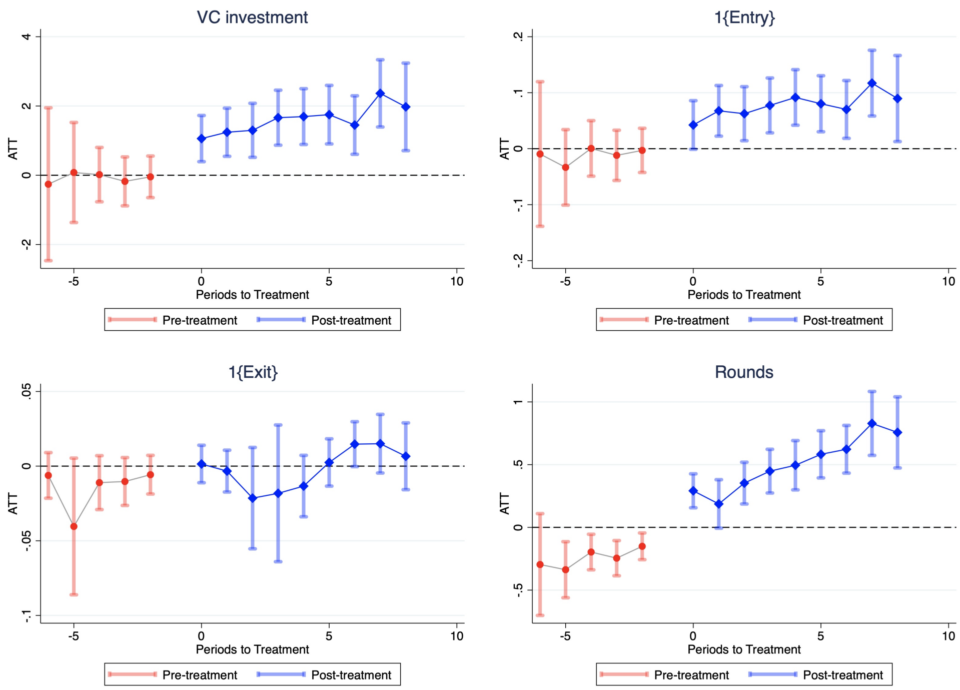


FIGURE A.3. Event-study using the staggered DiD

Notes: The plots refer to our preferred specification, which is the one wherein we match on the covariates in Z_i, estimated in the main sample. The confidence intervals shown are at the 95% level. Contaminated controls are excluded from the regression.

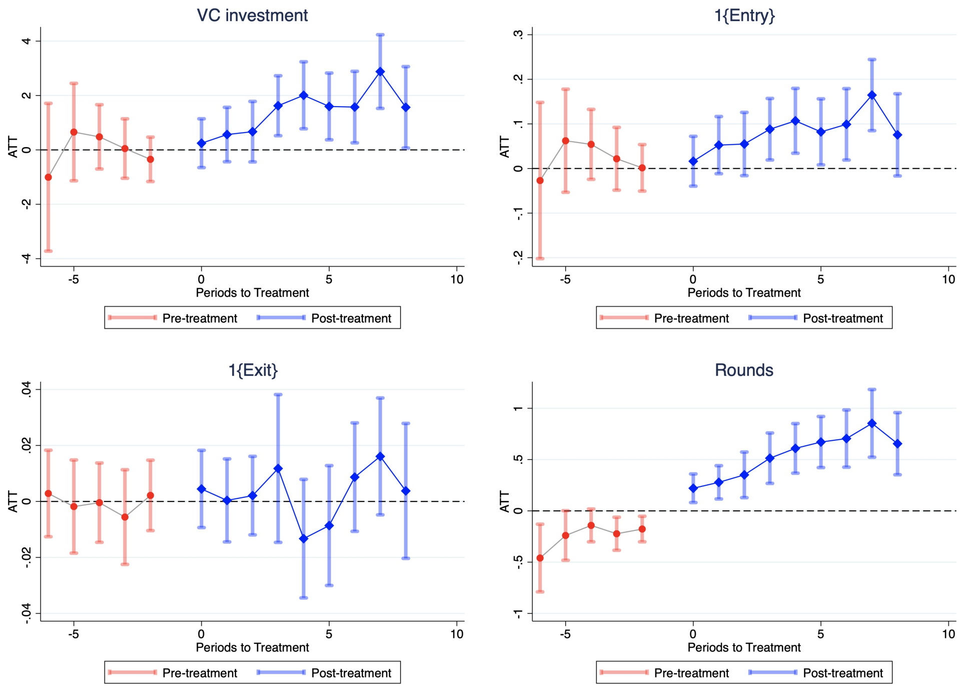


FIGURE A.4. Event-study in Alternative sample 1 using the staggered DiD

Notes: The plots refer to our preferred specification which is the one wherein we match on the covariates in Z_i. The confidence intervals shown are at the 95% level. Contaminated controls are excluded from the regression.

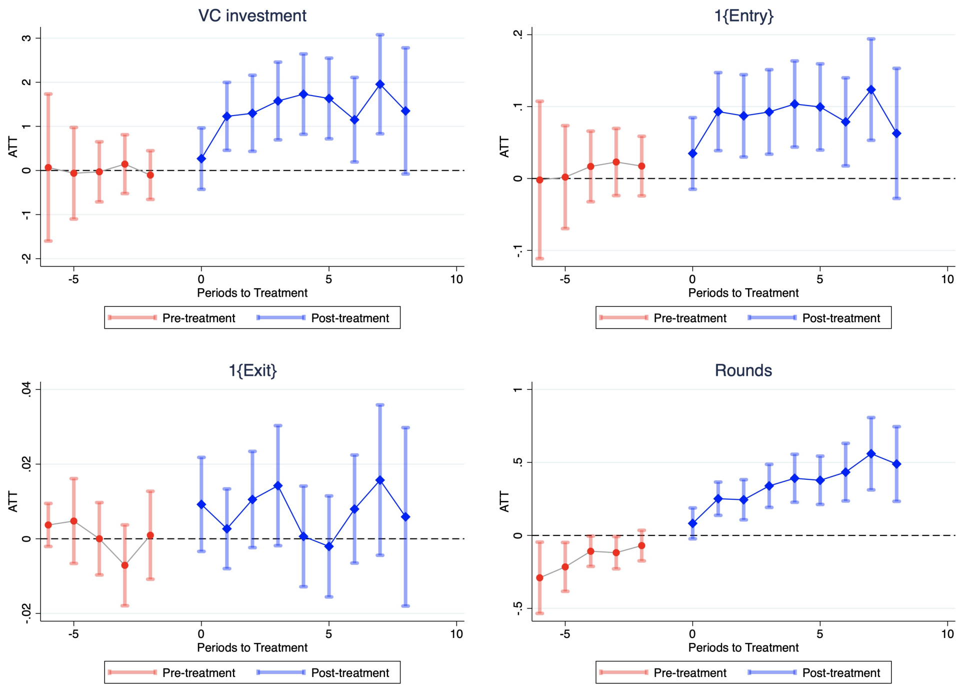
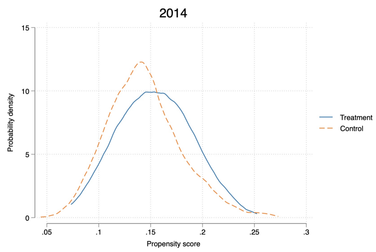
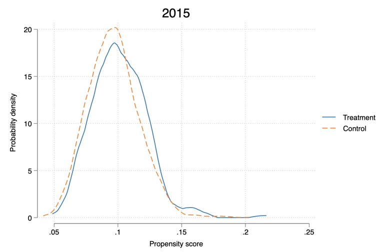


FIGURE A.5. Event-study in Alternative Sample 2 using the staggered DiD

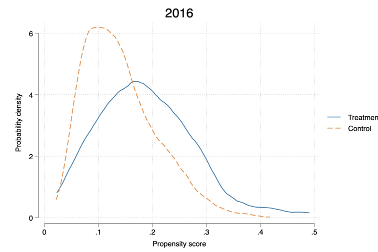
Notes: The plots refer to our preferred specification which is the one wherein we match on the covariates in Z_i. The confidence intervals shown are at the 95% level. Contaminated controls are excluded from the regression.



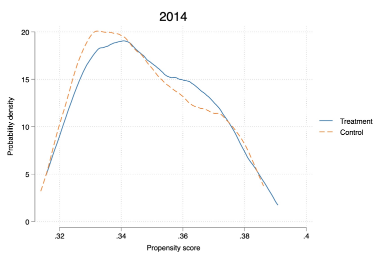
A. Main sample



B. Main sample

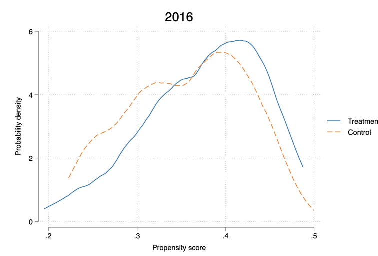


C. Main sample

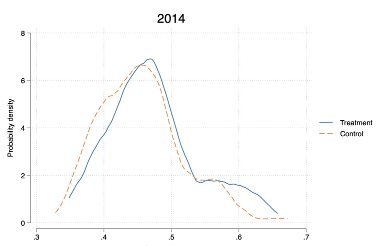


D. Alternative Sample 1

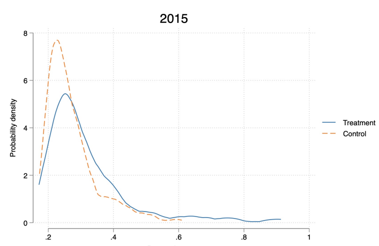
E. Alternative Sample 1



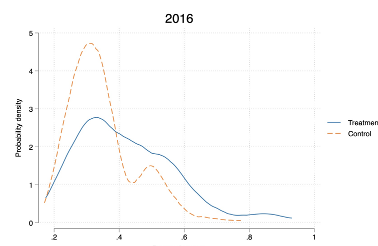
F. Alternative Sample 1



G. Alternative Sample 2



H. Alternative Sample 2

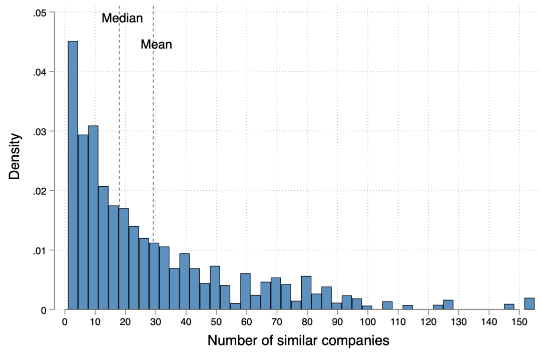


I. Alternative Sample 2

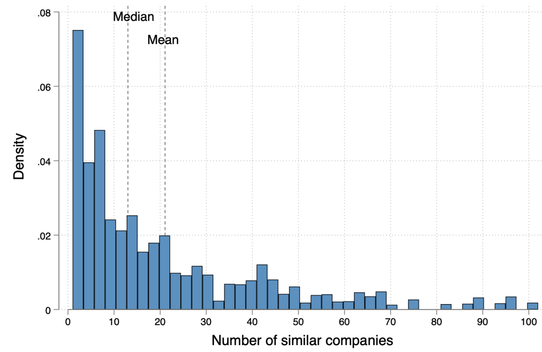
FIGURE A.6. Distribution of the propensity score across samples and merger-years

Notes: In the plots, control units include contaminated controls for the main sample and Alternative Sample 1, whereas they are excluded from Alternative Sample 2.

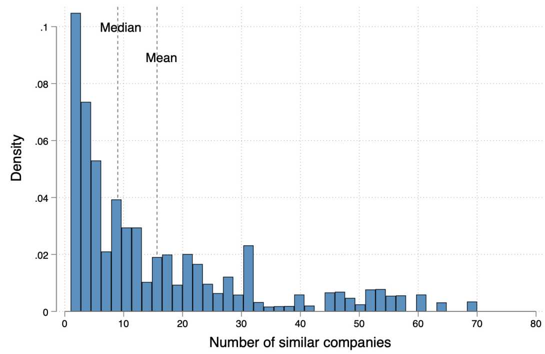
Appendix B. Additional Robustness Analyses: Similarity Thresholds



A. Similarity = 0.40



B. Similarity = 0.45



C. Similarity = 0.50

FIGURE B.1. Distribution of similar companies using different similarity thresholds

TABLE B.1. Summary statistics with different similarity thresholds

	Treatment				Control				Contaminated Control			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	N	mean	sd	median	N	mean	sd	median	N	mean	sd	median
Panel A: 0.40 Similarity threshold												
Focal target year founded	750	2,006.13	4.59	2,007	1,825	2,005.18	4.70	2,006	3,407	2,005.13	4.65	2,006
BIN pre-M&A # of rounds	750	4.05	7.94	2	1,825	1.21	1.87	1	3,407	4.95	8.17	2
BIN pre-M&A VC investment (USD M)	750	34.50	83.57	4	1,825	12.33	65.35	0	3,407	47.34	114.02	6.72
Focal target pre-M&A # of rounds	750	2.45	1.68	2	1,825	2.01	1.43	1	3,407	1.94	1.29	1
Focal target pre-M&A funds (USD M)	750	23.76	36.23	11.50	1,825	18.91	25.74	9.50	3,407	18.03	23.77	9
Predicted M&A probability	746	0.04	0.07	0.02	1,812	0.02	0.02	0.01	3,391	0.04	0.07	0.03
Panel B: 0.45 Similarity threshold												
Focal target year founded	524	2,006.07	4.62	2,007	1,580	2,005.07	4.69	2,006	2,089	2,005.14	4.68	2,006
BIN pre-M&A # of rounds	524	2.91	5.61	1	1,580	1.07	1.75	0	2,089	3.88	6.63	2
BIN pre-M&A VC investment (USD M)	524	25.80	66.75	2.40	1,580	10.14	48.21	0	2,089	37.55	94.49	4.54
Focal target pre-M&A # of rounds	524	2.49	1.66	2	1,580	1.99	1.40	1	2,089	1.92	1.28	1
Focal target pre-M&A funds (USD M)	524	24.69	38.31	12	1,580	18.58	25.54	9	2,089	18.12	24.01	9
Predicted M&A probability	503	0.03	0.06	0.01	1,502	0.01	0.02	0	1,991	0.03	0.07	0.01
Panel C: 0.5 Similarity threshold												
Focal target year founded	354	2,006.15	4.72	2,007	1,273	2,005.20	4.72	2,006.00	1,102	2,005.18	4.63	2,006
BIN pre-M&A # of rounds	354	2.15	4.16	1	1,273	1.03	1.71	0	1,102	3.22	5.44	1
BIN pre-M&A VC investment (USD M)	354	19.16	53.28	0.08	1,273	9.67	42.21	0	1,102	33.19	84.62	2.54
Focal target pre-M&A # of rounds	354	2.39	1.60	2	1,273	1.91	1.32	1	1,102	1.93	1.28	1
Focal target pre-M&A funds (USD M)	354	23.05	33.38	11.05	1,273	17.49	22.50	9	1,102	18.45	24.86	8.63
Predicted M&A probability	342	0.02	0.04	0.01	1,209	0.01	0.02	0	1,052	0.03	0.07	0.01

Notes: The table displays summary statistics for the key variable characterizing focal targets and BINs in the main sample. In Panel A BINs are defined using a 0.40 cosine similarity threshold as in our main analyses. Panel B and C show the change in the statistics when cosine similarity thresholds of 0.45 (Panel B) and 0.50 (Panel C) are used.

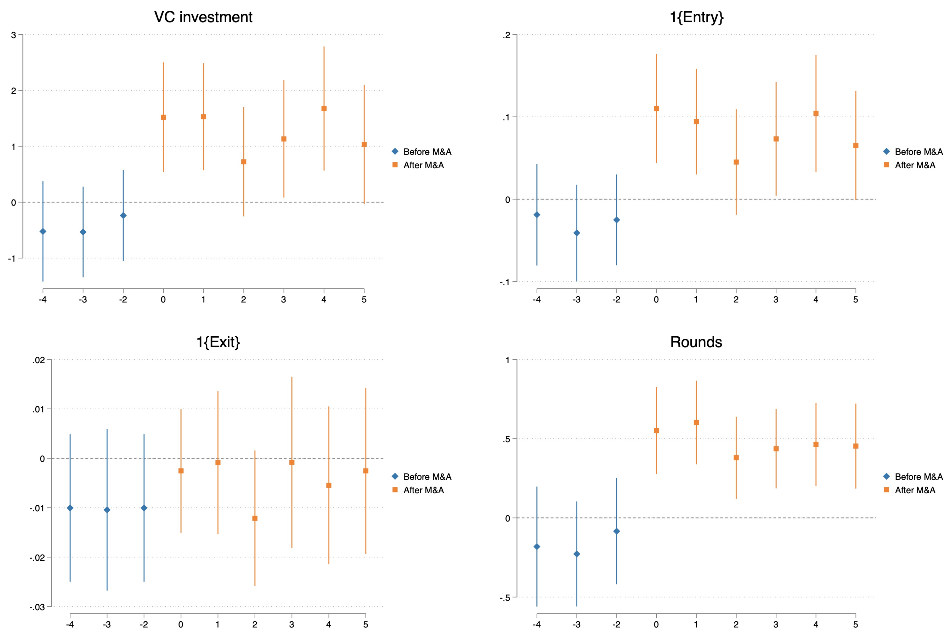


FIGURE B.2. Event-study for the effect of M&A with 0.5 similarity threshold

Notes: The plots refer to our preferred specification, which is the one wherein we include $Z_i \times Post_t$, estimated in the main sample. The confidence intervals shown are at the 95% level. Contaminated controls are excluded from the regression.

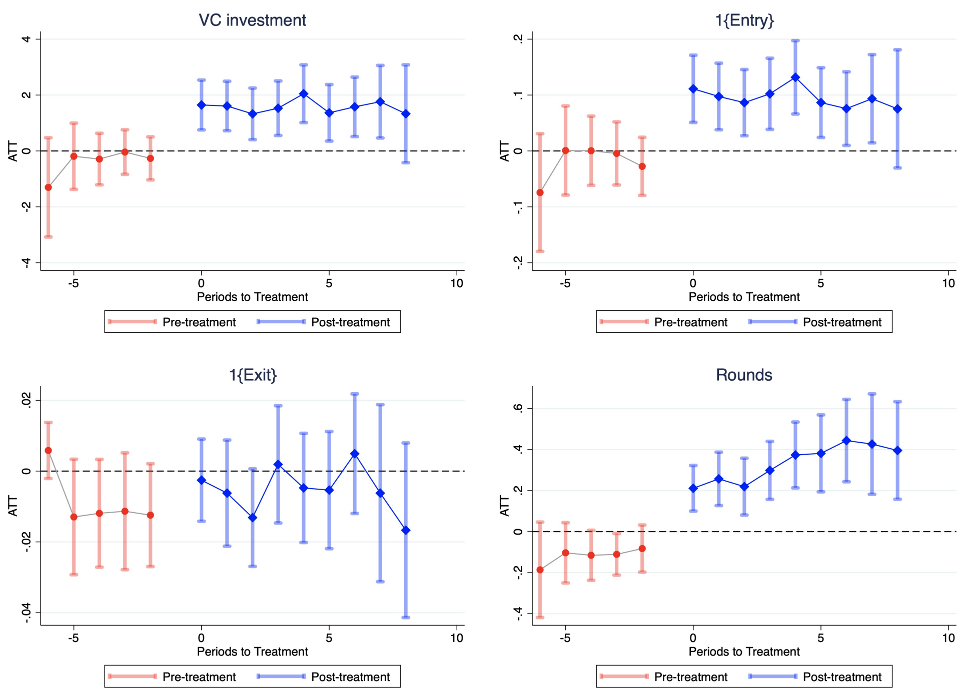


FIGURE B.3. Event-study for the effect of M&A using staggered DiD and 0.5 Similarity Threshold

Notes: The plots refer to our preferred specification, which is the one wherein we include $Z_i \times Post_t$, estimated in the main sample. The confidence intervals shown are at the 95% level. Contaminated controls are excluded from the regression.

TABLE B.2. Average effect of M&A using different cosine similarity thresholds

VARIABLES	(1) VC investment	(2) VC investment	(3) 1{Entry}	(4) 1{Entry}	(5) 1{Exit}	(6) 1{Exit}	(7) Rounds	(8) Rounds
Panel A: 0.40 Similarity threshold								
Treatment × Post	1.395***	1.415***	0.0514***	0.0686***	0.00175	0.00305	0.00487	0.375***
	(0.218)	(0.229)	(0.0137)	(0.0147)	(0.00275)	(0.00269)	(0.0517)	(0.0590)
Observations	25,750	25,580	25,750	25,580	25,750	25,580	23,000	22,840
R-squared	0.392	0.393	0.354	0.356	0.128	0.129		
Panel B: 0.45 Similarity threshold								
Treatment × Post	1.211***	1.371***	0.0667***	0.0888***	0.000316	0.00385	0.0392	0.415***
	(0.254)	(0.268)	(0.0163)	(0.0174)	(0.00277)	(0.00280)	(0.0688)	(0.0788)
Observations	21,040	20,050	21,040	20,050	21,040	20,050	18,400	17,530
R-squared	0.345	0.350	0.319	0.322	0.126	0.128		
Panel C: 0.50 Similarity threshold								
Treatment × Post	1.401***	1.592***	0.0837***	0.103***	0.00391	0.00356	0.181**	0.565***
	(0.294)	(0.304)	(0.0187)	(0.0195)	(0.00295)	(0.00272)	(0.0913)	(0.101)
Observations	16,270	15,510	16,270	15,510	16,270	15,510	13,910	13,280
R-squared	0.330	0.331	0.303	0.307	0.119	0.119		
BIN FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
$Z_i \times Post$	NO	YES	NO	YES	NO	YES	NO	YES
Poisson							✓	✓
Mean	5.402	5.402	0.381	0.381	0.0139	0.0139	0.952	0.952

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table displays the results obtained from estimating the TWFE model in Equation 1 in the main sample, excluding contaminated controls, comparing the cases wherein BINs are defined using a 0.40 (Panel A), a 0.45 (Panel B), or a 0.50 (Panel C) cosine similarity threshold. The odd-numbered columns present the results without controlling for $Z \times Post$. The even-numbered columns include such controls on the right-hand side. Robust standard errors in parentheses are clustered at the focal target level.

Table B.3. Average effect of M&A using staggered DiD and different cosine similarity thresholds

DEP. VAR.	(1) ATT	(2) SE	(3) ATT	(4) SE	(5) Mean
Panel A: 0.40 Similarity Threshold					
VC investment	0.958***	0.257	1.547***	0.305	6.062
1{Entry}	0.033*	0.017	0.075***	0.019	0.416
Rounds	0.513***	0.065	0.473***	0.072	1.126
1{Exit}	0.004	0.004	-0.003	0.008	0.017
Observations	33,254		33,254		
Panel B: 0.45 Similarity Threshold					
VC investment	0.460	0.305	1.375***	0.345	5.162
1{Entry}	0.013	0.020	0.077***	0.022	0.360
Rounds	0.325***	0.064	0.363***	0.069	0.825
1{Exit}	-0.001	0.005	0.003	0.006	0.012
Observations	27,352		27,352		
Panel C: 0.50 Similarity Threshold					
VC investment	0.852**	0.360	1.589***	0.367	4.437
1{Entry}	0.041*	0.024	0.097***	0.024	0.314
Rounds	0.256***	0.060	0.325***	0.062	0.631
1{Exit}	-0.004	0.006	-0.004	0.006	0.001
Observations	20,163		20,163		
Match on covariates			✓		

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table displays the results obtained from the staggered DiD model in the main sample, excluding contaminated controls, comparing the cases wherein BINs are defined using a 0.40 (Panel A), a 0.45 (Panel B), or a 0.50 (Panel C) cosine similarity threshold. Column 1 shows the ATT without controlling for $Z \times Post$, whereas column 3 includes such controls on the right-hand side. The respective robust standard errors are reported in even-numbered columns and clustered at the focal target level.