Venture Capital and Intangible Capital*

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Abstract

How is the financial sector linked to investment in intangible capital? To study this question, we build a data environment that connects diverse capital market intermediaries that channel investor savings into firms' productive investments across a range of technologies. We find that a particular type of financial intermediary—venture capital (VC) funds—is uniquely positioned to finance intangible investment. We provide both macro- and micro-level empirical evidence that changes in VC activity strongly predict changes in intangible investment—in both research and development as well as sales and marketing—and value among younger cohorts of firms. We do not find similar patterns for tangible investment, nor financing of intangibles by debt investors, private equity funds, or corporate investors. Our evidence suggests that VC finances intangibles both by reallocating capital to scale young firms in industries with intangible-intensive technologies and by shifting employment toward roles that support intangible investment.

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A successful financial system channels savings into productive investment, thereby facilitating economic growth. But what happens if the nature of investment changes? Over the past 40 years, business investment in intangible capital has increased dramatically, sparking a large literature on whether or not intangible investment can be as easily financed as more tangible capital (e.g., Dell'Ariccia, Kadyrzhanova, Minoiu and Ratnovski (2021); Falato, Kadyrzhanova, Sim and Steri (2022); Li (2025); He (2025)). A lesson from this body of research is that the financing of intangible capital may require a re-organization of the financial system and a shift in the type of financial intermediaries that facilitate economic growth.

This study presents robust empirical evidence that venture capital is a crucial financial intermediary in this increasingly intangible capital world. The strong association between venture capital and intangible capital is present across many settings: intangible capital value of firms conducting an initial public offering, evidence on the type of industries targeted by venture capital, and microeconomic evidence using the composition of the workforce of firms that receive an initial venture capital investment. In all of these settings, venture capital financing is directly tied to investment in intangible capital, both knowledge capital and customer capital. Furthermore, while it is widely acknowledged that venture capital is crucial to the development of knowledge capital through the financing of research and development, this study shows that venture capital also is critical to the financing of sales and marketing expenditures that ultimately produce substantial customer capital value. In contrast, the tight relationship between venture capital and intangible capital does not exist for other financial intermediaries such as private equity, debt, or corporate investors, highlighting the unique role of venture capital.

First, we build a rich data infrastructure studying how different capital market intermediaries (e.g. VCs) channel savings between investors (e.g. pension funds) towards productive investments by firms using different technologies. We trace back firms' real investment, worker composition, size, and enterprise value to the history of private capital market deals they received over their life cycle since birth. We measure investments in tangible capital, via expenditures on equipment and structures, as well as intangible capital, via expenditures on sales and marketing (S&M) and research and development (R&D) directly when possible; otherwise, we use measures from employment in S&M or R&D roles.

We start with motivating facts that VC-backed firms have significantly higher rates of intangible investment relative to their size–but not higher tangible investment–as well as higher levels of Tobin's "Q," a measure of intangible value: enterprise value relative to the physical capital stock.

Importantly, when looking among firms backed by other financial intermediaries that are not VCs, such as PE investors, we do not find the higher levels of intangible investment nor value we find for VC-backed firms.

Given that VC-backed firms tend to have disproportionately higher rates of intangible investment and value, we investigate whether the observed increase in the share of economic activity concentrated in VC-backed firms account for the increasing importance of intangible capital investment. Using an aggregate decomposition accounting identity, we find that among public firms in cohorts born after 1990, the increase in the sales share of VC-backed firms alone can account for most of the rise in intangible investment and "Q".[1]

We then move on to more granular empirical tests using our data on both private and public firms. First, among firms undergoing IPOs, we find a strong link between venture capital (VC) financing and intangible capital investment. VC-backed firms invest significantly more in both R&D and S&M, pre- and post-IPO, while no similar pattern appears for physical capital or for firms financed by private equity or debt. This relationship holds across industries and over time and is reflected in higher measures of intangible value, with VC-backed firms consistently exhibiting larger "Q" valuations relative to their physical capital.

Next, we estimate the causal impact of VC supply at the state–sector level on employment among firms of varying age and industry intangibility using a shift-share design. The instrument exploits annual growth in state public pension funds' assets under management as a shifter, leveraging their documented home bias to generate plausibly exogenous variation in VC funding originating from in-state investors. Exposure shares are constructed from each VC's historical allocation across states and two-digit NAICS sectors over the previous decade, capturing persistent geographic and industry specialization. Our results indicate that VC financing is particularly effective at scaling young firms in high-intangible industries, with no effects observed for firms older than 10 years or for firms in industries that are not intangible-intensive.

Finally, we use a firm-level stacked difference-in-differences design to show that VC investments are associated with increased employment growth among portfolio companies overall and across intangible-related positions, including both R&D and S&M. In contrast, firms receiving debt financing or other forms of equity investment that often involve concurrent debt investments (i.e. PE

[1]While we show this in public firm data using sales and firm-level measures of intangible investment and VC-backing, aggregate data from the national accounts shows a similar increase in share of value added of sectors where VCs concentrate, where the largest (and rising) share of intellectual property investment is done.

deals) or corporate investments do not exhibit similar increases in overall scale or in intangible-related positions.

Ultimately, changes in intangible capital can arise either from the scaling of firms that already rely on intangible-intensive technologies (composition effects) or from shifts in the technology itself (direct and reallocation effects). We find evidence for both, but their importance varies across the firm life cycle. The patterns observed at higher-levels of aggregation suggest composition effects dominate, with large increases in firm scale following VC financing reallocating resources towards intangible intensive firms. However, difference-in-differences estimates at the lowest level of aggregation we can observe reveal a different margin. Around VC investment, firms not only scale up but also change their input mix, with sizable reallocations toward R&D and S&M intangibles. These technology shifts are most pronounced early in the life cycle, when the firms' technology may still be malleable. We do not observe non-VC intermediaries, which tend to target more mature firms, having these effects on the input mix. Moreover, while the literature has traditionally emphasized R&D, a novel aspect of our findings is that S&M plays an equally large and more persistent role, continuing to expand after VC investment.

Related literature

This paper contributes to the longstanding literature that has long emphasized venture capital as a central funding source for high-risk, high-growth startups. A well-established finding is that VC investors primarily invest in risky ventures with highly skewed, "Power Law" return distributions where most startups fail, and therefore fund performance is driven by a small number of outsized successes (e.g., Winton and Yerramilli (2008); Gompers, Gornall, Kaplan and Strebulaev (2020). This skewness is accompanied by a "J-curve" pattern in returns, reflecting a trade-off between short-term losses and long-term gains (e.g., Hellmann et al. (2024)).

Beyond financing, VCs play a critical role in fostering growth and innovation by channeling resources toward high-potential startups, thereby shaping technological progress and industry dynamics (e.g., Kortum and Lerner (2000), Hall and Lerner (2010); Puri and Zarutskie (2012); Lerner and Nanda (2020); González-Uribe (2020); Aragoneses and Saxena (2025); Matray (2021)). Our paper most closely relates to work on the value-added roles of venture capitalists in early-stage firms. Prior research shows that VCs mitigate information asymmetries through sophisticated contracting (e.g., Hellmann (1998); Kaplan and Strömberg (2003); Kaplan and Strömberg (2004)) and through active monitoring (e.g., Gompers (1995); Lerner (1995); Bernstein, Giroud and Townsend

(2016); Gompers, Gornall, Kaplan and Strebulaev (2020)).

Moreover, several studies document that VCs also contribute to the professionalization of startups by helping founders identify product–market fit, standardizing business practices, facilitating customer introductions, and supporting key executive hires such as marketing leadership (e.g., Hellmann and Puri (2000); Hellmann and Puri (2002); Kaplan, Sensoy and Strömberg (2009); Gompers, Gornall, Kaplan and Strebulaev (2020)). Our paper builds most directly on this latter strand by providing evidence that VCs finance intangibles both by reallocating capital to scale young firms in industries with intangible-intensive technologies and by shifting employment toward intangible-related roles such as research and development as well as sales and marketing.

Our findings are also related to the literature on private equity.[2] In particular, Bloom et al. (2015) document that "plant managers in private equity–owned firms report greater autonomy from headquarters over sales, marketing, and new product introduction," which is consistent with our results on the sales and marketing component of intangibles. Jang, Kim and Sufi (2025) also show that both private equity and private credit specialize more in intangible-intensive industries than traditional lenders. Hence, the null effects we find of private equity on intangible investment are noteworthy. One possible explanation is that these results reflect differences in firms' age distributions (e.g., the median firm age at the first VC deal is 2, compared with 18 at the first PE deal) or the concurrent use of debt (e.g. in leveraged buyouts) with capped upside.

This work relates to the literature on intangible capital at the intersection of macroeconomics and finance (e.g. Crouzet, Eberly, Eisfeldt and Papanikolaou (2025); Belo, Li, Salomao and Vitorino (2024); Ottonello and Winberry (2024); Crouzet and Eberly (2023); Peters and Taylor (2017); Gutiérrez and Philippon (2016); Falato, Kadyrzhanova, Sim and Steri (2022); McGrattan and Prescott (2010); Midrigan and Xu (2014)). This study shows that not all financial intermediaries are well-positioned to finance intangible capital; instead, venture capital firms fulfill a unique role. Furthermore, the results showing that venture capital finances customer capital by facilitating higher sales and marketing expenditures is, to the best of our knowledge, new to the literature.

Overall, the results presented here highlight that the financial intermediation sector includes different intermediaries that may specialize in financing particular types of capital, and intangible capital in particular. This is reminiscent of Baqaee and Farhi (2018)'s revival of Samuelson (1966)–

[2]Prior work provides empirical evidence that private equity affects firm and employment outcomes through changes in resource allocation, monitoring, and operational support (e.g., Davis, Haltiwanger, Handley, Jarmin, Lerner and Miranda (2014), Gompers, Kaplan and Mukharlyamov (2016), Davis, Haltiwanger, Handley, Lerner, Lipsius and Miranda (2021), Herkenhoff, Lerner, Phillips, Rebelo and Sampson (2025)).

who famously conceded "capital could not be aggregated" because of technology "re-switching," a particular instance of which we provide in the context of the interplay between venture capital and intangible capital.

1 Data

In this section, we describe the main data sources used in this study. We triangulate across multiple data sets often used separately to build a rich data infrastructure that allows us to trace out how different capital market intermediaries channel savings towards productive investments by firms using different technologies. We trace back firms' real investment, worker composition, size, and enterprise value to the history of all private capital market deals they received over their life cycle since birth. We measure investments in intangible capital either directly, or indirectly via the workers firms hire across heterogeneous roles related to intangibles.

Data linkage procedure. We use recent computational advances in LLM and text-based matching and within-state fuzzy matching with the LinkTransformer algorithm Arora and Dell (2023) in a procedure described in the Appendix.

1.1 Measurement of Private Capital Market Investment

We use a single widely-used industry source of private capital markets:

PitchBook. We gather information on US companies with a history of private financing deals from PitchBook. We use information on VC deals, as well as deals related to PE, debt, and several forms of corporate investments. We also the timing of deals and associated information such as the identity of the companies and investors involved, as well as available information on exits such as IPO and M&A. We also track all commitments from limited partners (LPs) into funds using PitchBook, in particular, the commitments of public pension funds.

1.2 Measurement of Economic Activity and Employment Composition

Our measurement of economic activity comes from different well-known data sources:

Revelio. We gather information on US companies with employment composition data from Revelio, which curates information from LinkedIn profiles and other similar sources. We work with both the Work Forced Dynamics and Profiles data which categorizes raw positions. The data

contains information at the "user" level, i.e. the individual worker in various positions, which we aggregate can aggregate at the firm-level.

BDS. We also use information from the Business Dynamics Statistics (BDS) which contains employment and number of firms across geography and industry cells in the US (e.g. NAICS 2 x state) for firm age groups (e.g. young firms under 10). This data comes from aggregating the Longitudinal Business Database (LBD) from the US Census Bureau.

BEA. We obtain aggregate data from the BEA on value added.

1.3 Direct Measurement of Investment Composition

We use standard sources to measure investment:

Compustat and Capital IQ. We supplement this data with information from both Compustat and Capital IQ, supplemented with data from SEC filings made by firms, on the financials of public companies post (and in some cases pre) IPO. In this sample, we are able to directly measure investment expenditures in physical capital (CAPEX), Research and Development (R&D), and Sales and Marketing. We are also able to measure the market value of companies used to construct "Q".

BEA. We obtain aggregate data from the BEA on disaggregate investment into physical capital and intellectual property.

1.4 LP Capital Supply

We collect data on the assets under management of state public pension funds from the State and Local Government Public-Employee Retirement Systems annual survey conducted by the U.S. Census Bureau. These funds represent a crucial source of capital for venture capital funds (Gonzales-Uribe and Balloch, 2021; Matray, 2021).

2 Measurement

In this section, we describe our measurement of intangible investment and VC at both dis-aggregate and aggregated levels separately. The core challenge is that while we observe VC financing history for both private and public firms, we only observe actual measures of intangible investment across all sectors in Compustat among firms that IPO at some point.

2.1 Intangible investment expenditure intensity for public companies

Our main measures of investment intensity (I/Y) come from Compustat and Capital IQ where we directly observe firms' expenditures in dollars in (a) Research and Development (R&D) derived from rd and (b) Sales and Marketing (S&M) derived from sgna. We use the adjustments to the raw variables proposed in He et al. (2024) to deal with 0s – resulting in variables called xrd and xsalesandmarketing, and divide each of these investment expenditure measures by a firm's sales in the same period. We can also construct similar measures for physical capital investment using capx. While we have Compustat data, our best measures are from after 1996 due to the requirements described in the above reference. For a smaller subset of firms these ratios are available while firms are private: different expenditures and sales are available before the IPO for a subset of firms that reveal these financial items in their S-1 filings. We have also explored measures of investment per employee rather than sales in alternative specifications.

2.2 Measurement of private financial intermediation

For a given firm either private or public, PitchBook allows us to track whether they engaged in a financing deal with a VC fund in a given year back since the founding of the firm. We can trace the firms' financing path until the IPO, and consider them VC-backed henceforth. We have also perform robustness with broader measures of VC financing that uses VC status information from other sources such as those from Jay Ritter used in Peters and Taylor (2017). Note we can do the same for other types of private investments such as PE the firm may have gotten in the past.

2.3 Sector-based measures of investment intensity and VC Activity

For each NAICS 2 and 3 codes we compute measures of the median (and size-weighted) mean of I/Y for both S&M and R&D relative to sales, and rank sectors according to their intangible investment intensity using public firm data from Compustat/Capital IQ. We categorize firms in sectors above the median in these measures (regardless of whether they are private or public) as being in high intangible intensive sectors. We repeat the same exercise using the propensity of firms being VC financed across sectors to categorize sectors into "VC-sectors" vs not.

2.4 Intangible value or "Q" for public companies

We follow Crouzet and Eberly (2023) in measuring intangible value defined as the enterprise value of the company relative to their stock of physical capital: $Q = V/K^P$. We use a standard measure of enterprise value V that add up equity and debt and rely on the data measures of physical capital rather than build our own (e.g. via a perpetual inventory method).

To build V we first use the market value of equity (or market capitalization) prcc $\times$ csho. prcc is the price close (fiscal year-end) and csho is the number of common shares outstanding. We add to this the book value of preferred equity pstk and minority interests mib. To this get at total firm value we add to equity the total value of debt, both long-term dltt and short-term dlc. From this measure of enterprise value we remove che, which are cash and short-term investments.

We also measure the physical capital stock of the company K^Pas gross property plant and equipment ppegt. For NAICS 3 236 (construction of buildings) we add inventories to the measure of capital stock.

2.5 Worker-based measures of intangible related positions for all companies

We match Revelio to PitchBook and Compustat using a mix of standard identifiers (e.g. CIK, EIN), text identifiers (e.g. company names and addresses), and links (e.g. Website URLs, LinkedIn usernames). We use the methodology in Arora and Dell (2023) to further improve matches. We thus observe a comprehensive network of at worker-firm level for firms present in PitchBook or Compustat. Within Revelio, we use various methods to flag positions as related to intangible capital investment and use aggregate counts or costs across those positions as a measure of intangible intensity. In the data, we have categorizations of the workers into sales and marketing, scientists, researchers, developers, engineers, and technicians. We focus mainly on the Workforce Dynamics subsample of the data, but also work with the full Positions Revelio data. For a later version of this paper, we are also working on splitting categorizing workers into $S\&M$ vs $R\&D$ positions exploiting both the text of positions and economic variables.

2.6 Aggregate measures of investment intensity

In the BEA data, we observe Value Added (VA), physical capital investment (equipment and structures) and one particular measure of intangible investment: intellectual property.

3 Motivating Facts

We start by motivating our more detailed analyses with aggregate data from the national accounts produced by the Bureau of Economic Analysis (BEA). We match sectors at the NAICS 3 level in the BEA with information derived from PitchBook and Compustat aggregated also at the NAICS 3 level.

3.1 BEA VA Shares of VC Backed Sectors

Figure 1 (top) presents evidence that economic activity has shifted since the 1980s towards sectors targeted by VCs measued by their share of value added (VA). We sort sectors by the share of firms that are VC-backed within the sector, and categorize sectors with above-median shares of firms targeted by VCs as "VC sectors".[3]

3.2 BEA Intangible investment and VC

Figure 1 (bottom) shows that the same sectors where VCs focus are those where a large share (around 80%) of intellectual property investment concentrates. Further, VC backed sectors seem to be where this often used proxy for intangible investments has been concentrating even further since the late 1990s, with some lag relative to their increase in the share of VA. No similar changes can be seen for the share of physical capital in VC-backed sectors, which if anything has decreased although not significantly so.

4 Descriptive Evidence on Venture Capital and Intangibles

We used data from our IPO sample matched with PitchBook to perform descriptive analyses that show a strong correlation between venture capital financing and intangible capital investment. In contrast, such association is not present for other financial intermediaries (such as PE or debt) nor for other forms of investment (i.e. physical capital).

[3]These sectors include 541 Professional and technical services, 518 Data processing, 334 Computer and electronics manufacturing, 518 Telecommunications, 519 Search, 513 Publishing, or 325 "Chemicals.

4.1 Venture Capital and Intangible Investment

The data shows clearly our main point: VC-backed firms have significantly higher rates of intangible capital investment; in contrast, no similar pattern can be found for physical capital. We present this fact using two different analyses that show how intangible and tangible I/Y varies with VC: cross-industry relations and taking a look at life cycle profiles pre-IPO. We also present post-IPO life cycle profiles in the Appendix.

Figure 2 shows the presence of VCs across industries – the share of firms that are VC backed within an industry – is highly predictive of the industry's intangible intensity in both S&M and R&D.

Figure 4 shows the fact highlighted across industries – that VC-backed firms are systematically more intangible intensive – is present pre-IPO for the sample of data in which accounting information on expenses in S&M and R&D is available before the firm starts trading publicly.

We do not find the same patterns found for intangible investment among VC-backed firms when looking at physical capital investment: Figure 5 shows no significant, systematic differences in physical capital (or tangible) investment intensity between VC backed and non-VC backed firms and industries. There is only slightly higher CAPX intensity among VC backed firms 2 years pre-IPO that quickly converges to that of non-VC backed firms. Across industries this relationship is if anything slightly negative.

Finally, Figure 6 compares the investment to sales ratios (physical capital capital expenditures vs intangible S&M and R&D) for VC vs non-VC backed firms in Compustat born after 1990 for which we have the best IPO data after 1997. This figure confirms VC backed firms have systematically higher intangible investment ratios than non-VC backed firms in both S&M and R&D. Further, it also confirms that the same difference between VC and non-VC backed firms does not arise for physical capital CAPEX investment.

In the Appendix, we show that these patterns for investment also hold for all firms in the post-1950 Compustat, not just the cohorts born after 1990. However, we show these investment facts are unique to venture capital: no similar patterns arise in the case of other forms of investments such as PE or debt.

4.2 Venture Capital and Intangible Value

We show that a measure of intangible value, Q, that is defined as the total enterprise value relative to the physical capital stock build via capx – which Crouzet and Eberly (2023) argue measures intangible capital value – is disproportionately high among VC backed firms.

Figure 3 thus shows the presence of VCs across industries is also highly predictive of the industry's intangible value measured both as median and average "Q".

Further, Figure 7 plots "Q" for VC versus non-VC firms over time and also shows this difference among VC-financed firms that exists for intangible investment is present as well for "Q" which is higher for VC-backed firms throughout among firms in Compustat born after 1990 for which we have the best IPO data after 1997.

In the Appendix, we show that this VC "Q premium" is also present in the full sample of firms from 1950 on (although smaller than for those born after 1990) but is not present categorizing firms that received other forms of financing such as PE or debt.

4.3 "Macro" Shift-Share: VC Activity and Intangible Investment and Value

We use a shift-share methodology to understand the data and the relationship between changes in VC activity and intangible investment and value finding venture capital to be a strong predictor of both of these phenomena.[4]

Formally, we measure investment relative to sales each years t in the group of firms g that are in cohorts born in 1990 or after within the Compustat sample of public firms. We focus on the cohorts of firms born after 1990 for which we have the best IPO data after 1997 in the main text and in the appendix we produce the same analyses for firms in the entire Compustat sample (highlighting the nuance that changes in VC activity are inherently biased towards firms in recent cohorts). For firms born after 1990 present in Compustat post 1997, we classify them by their investor i status according to whether they ever received VC backing or not.

$$I_{gt}/Y_{gt} = \sum_{i \in \{\text{VC, Non-VC}\}} (Y_{igt}/Y_{gt}) \cdot (I_{igt}/Y_{igt})$$

[4] A similar shift-share methodology has been used in other questions around asset markets like Mian et al. (2021) who study shifts in the household income distribution, Auclert et al. (2021) who study shifts in the household age distribution, and Aragoneses (2023) who studies shifts in the firm age distribution.

Furthermore, we can measure Q within the group by investor class using physical capital shares rather than sales shares given Crouzet and Eberly (2023):

$$V_{gt}/K^P_{gt} = \sum_{i \in \{\text{VC, Non-VC}\}} \left(K^P_{igt}/K^P_{gt}\right) \cdot \left(V_{igt}/K^P_{igt}\right)$$

Figures A7 and A6 in the Appendix confirms the shift in the distribution of economic activity towards VC-backed firms documented in the BEA data in Figure 1 is also present among the cohorts of firms born after 1990 in Compustat – as well as for all cohorts – using sales (and employment or physical capital). We use these changes in the share of sales concentrated among VC-backed firms in Compustat to show what the composition shift towards VC-backed firms implies about changes in intangible investment and value.

To measure these composition changes, we apply the formulas above holding constant the ratios we can measure in 1997 (I_{ig0}/Y_{ig0}) but allow the shares of economic activity concentrated in VC vs non-VC backed firms to change from 1997 to 2024: (Y_{igt}/Y_{gt}).

Intangibles and the Concentration of Economics Activity on VC-Backed Firms. Figure 8 shows the shift in the distribution of economic activity towards VC-backed firms alone, when coupled with the fact that VC-backed firms have higher intangible intensity, can account to a larger extent for the increase in intangible investment intensity among the sample of firms born after 1990 in Compustat. The direct effect, which holds constant these shares and looks at ratios, is negligible due to the fact that these ratios are roughly stationary. Breaking down intangibles into R&D and S&M shows the shift in the VC sales share has been a driver for both at low-frequencies and direct effects if anything have depressed intangible investment intensity. In contrast, for physical capital investment, the direct effect of VC are

Figure 9 documents that the same shift in the distribution of economic activity towards VC-backed firms among the cohorts born after 1990 can also account for the increase in "Q", measured as value per unit of physical capital following Crouzet and Eberly (2023).

Repeating this exercise beyond the firms born after 1990 and looking at the entire sample shows among all firms in the economy the composition shift in the sales distributions towards VC-backed firms accounts for roughly [2/3] of the rise of the intangible/sales ratio. In contrast, the VC composition effects in the overall sample for changes in Q are much weaker than in the sample with only firms born after 1990.

Put together, these descriptive analyses show a clear connection between changes in VC-backed

activity and intangible capital investment and value. Although purely descriptive, they set the stage for the causal analyses we perform below.

5 Causal Evidence on the Impact of Venture Capital

In this part of the paper, we present several analyses on the differential impact of VC investments on VC-backed firm scale and across measures of intangible investment: a stacked differences-in-differences (DID) strategy at the firm-level and a shift-share instrumental variables design at the sector-region level. We use PitchBook together with Revelio and US Census data from the BDS, which contains information on all firms (public and private) for our analyses.

5.1 "Micro" Shift-Share: Instrumenting for VC Supply

In this section, we present sector–state-level analyses of the causal impact of VC supply on economic activity. Our identification strategy relies on a shift-share empirical design.

As the shifter, we use the annual growth in the assets under management (AUM) of state public pension funds to instrument for changes in VC deal flow originating from investors headquartered in states exposed to pension fund growth. This is motivated by the well-documented "home bias" of public pension funds, which tend to invest in funds headquartered within the same state (González-Uribe, 2020; Matray, 2021).

For the shares, we construct, for each year, the portfolio shares of each VC investor across states and sectors (NAICS 2-digit), based on the previous ten years of deals recorded in PitchBook. This is motivated by the tendency of VCs to specialize in specific industries and geographies, implying that they are likely to continue investing in similar types of deals as they raise additional funds.

Formally, let $Exposure_{j,t}$ denote VC investor j's exposure to home-state public pension fund growth in year t, and let $\theta_{s,i,j,t}$ denote VC investor j's portfolio share in state s and industry i in year t, based on the previous ten years of deals. The resulting shift-share instrument at the state-sector level is then constructed as the sum, over all VC investors active in the given state-sector, of the product of each investor's shift and share:

$$Exposure_{s,i,t} := \sum_{j} \theta_{s,i,j,t} \times Exposure_{j,t} \tag{1}$$

First stage impact of Public Pension LP Growth on VC deals. Figure 13 illustrates the first-stage effect of our shift–share measure on VC deal flow, measured as the inverse hyperbolic sine of the total number of VC deals in each state–sector.[5] The figure shows a positive effect of exposure to pension capital supply on state-sector VC deals, significant in the year of the shock and persisting for one year thereafter. While both effects are present, we use the one-year lagged pension capital supply exposure to predict VC deals in our main IV regressions below, to ensure greater exogeneity.

$$\text{First Stage: } VC_{s,i,t} = \alpha + \beta Exposure_{s,i,t-1} + FEs + \epsilon_{s,i,t} \tag{2}$$

$$\text{Second Stage: } Employment_{s,i,t} = \alpha + \beta \widehat{VC_{s,i,t}} + FEs + \epsilon_{s,i,t} \tag{3}$$

Second stage impact of VC deal flow on employment and by industry intangible intensity. Table 1 and Table 2 presents the IV results using current year and prior year VC activity as the predicted regressor, respectively. The outcome variable is total employment at young firms (ages 0-10) at the state-sector level, drawn from the BDS data. As shown in the first column of both tables, the first-stage F-statistics exceed 10, indicating that the instruments pass the weak instrument test.

Both tables present a consistent picture: increases in VC deal flow induced by the pension LP supply shock lead to changes in employment among young firms (ages 0-10) within the same state–sector cell. This effect is observed only in high-intangible industries, that is, those with above-median sales and marketing expense ratios (from He et al. (2024)).[6] Interestingly, as shown in Tables 3 and 4, we find null effects on employment at older firms (i.e., firms older than 10 years), highlighting a life-cycle dimension in the impact of VC.

Overall, the results point to substantial heterogeneity in the effect of VC investments on firm activity. VC financing appears particularly effective at scaling young firms in high-intangible industries.

[5]The regressions include state-by-year, sector-by-year, and state-by-sector fixed effects and are estimated using two-way clustering at the state and sector levels.

[6]For the subsample analyses focusing on tangible and intangible sectors only, we cluster standard errors at the state level due to too few sector-level clusters.

5.2 Stacked Differences-in-Differences Decomposition

In this section, we present firm level analyses on the impact of VC investments on the firm employment relative to other forms of financing such as debt. We show how the employment composition changes following the investments using positions associated with intangibles. We perform these analyses in the Workforce Dynamics sample of Revelio for which we can observe intangible-related position categorizations.[7] We use a stacked DID specification that holds fixed the baseline employment of firms before the investment tracing out post-investment employment growth across all positions and on intangible-related positions.

In particular, we use the following specification. We stack firms treated in a given year s (e.g. 2014) and let the calendar year t run pre-post treatment where we define event time $t - s$ as the time since the first VC investment a firm in the PitchBook-Revelio match receives. Each stack is treated as a separate sub-experiment and fixed effects are added at the firm-stack and year-stack level.

$$Y_{it} = \alpha_{i,s} + \gamma_{t,s} + \sum_{k=-\kappa_{\text{pre}}=-2}^{\kappa_{\text{post}}=5} \beta_k \cdot \mathbf{1}\{t - s = k\} \cdot D_i^s + \varepsilon_{it}$$

In practice, when letting studying employment as an outcome, we measure the total positions at the firm scaled by total positions at t-1. We further decompose these total effects across different position categories (e.g. sales and marketing). Event when performing decompositions, we continue to scale by outcomes at t-1. When looking at employment shares across different positions we do not scale by anything. We explore regressions with and without fixed effects by age, industry, and the combination of the two. We also perform treatment effect heterogeneity by investor asset class (e.g. VC, PE) and investment stage (e.g. first investment, second investment and so on).

Total Employment and Intangible-Related Positions Growth after VC Investment. Figure 14 shows that employment rises after a firm's first VC investment, with a substantial share of the increase concentrated in intangible-related positions. These effects grow and persist over time, and the absence of a pre-trend suggests they are not driven by VCs selecting firms already on this trajectory. While the figure highlights overall scaling across positions, it does not reveal whether firms adjust their employment mix. For this, we examine changes in employment shares directly.

Post-investment Changes in the Intangible Share of Employment for VC-Backed Firms.

[7] Results based on the full Profiles data with custom categorizations of the positions by how related to intangibles they are will be added in later iterations of this paper. We are also working on a control matching design using the general NETS data set.

Figure 15 shows that, beyond scale effects, VC investment leads to significant and persistent increases in the share of employment devoted to intangible activities. Four years after investment, the share rises by nearly 8% (from a baseline of 50%, a 16% relative increase). This shift reflects roughly equal contributions from knowledge and capital workers, each increasing by about 4%.[8]

No Comparable Effects after PE, Debt, or Corporate Investments. In contrast, Figures 17 and 18 show that investments by private equity, private credit, or corporate investors (e.g. acquisitions and CVC) are not associated with increases in overall employment or in intangible-related positions.

Overall, these findings point to distinct effects of VC financing: it expands firm scale and shifts employment toward intangible-intensive activities, consistent with changes in production technology rather than simple resource expansion. No similar patterns emerge following other forms of investment.

6 Conclusion

We find that not all types of financial intermediaries are equally well positioned to support intangible investments–research and development as well as sales and marketing. In particular, venture capital appears uniquely suited to financing intangible capital relative to debt-oriented or debt-like private equity (PE) funds, as well as other financial intermediaries, including corporate investors. Our empirical evidence shows that VC funds are not only more specialized in intangible-intensive firms but also more likely to disproportionately help scale overall employment at portfolio companies focused on intangibles and reallocate their technology further towards intangible-related positions. These outcomes are unique to the intersection of VCs and intangibles: no other financial intermediaries show similar patterns, and part of our evidence highlights them to be different for tangible capital investment.

A promising avenue for future research is to better understand the role of venture capital in supporting intangible asset growth and how different investment strategies shape firm outcomes. For instance, VCs may be particularly well-suited for financing intangible investments due to the "power law" nature of returns, where a few successful investments offset many failures. Debt or debt-like investors, such as PE funds, typically face capped upside, prioritize downside protection,

[8]The post-investment dynamics differ across these categories: R&D rises quickly but plateaus, while S&M grows steadily and persistently even as R&D slows. We are currently exploring these patterns in later-stage VC investments.

and seek stable cash flows, whereas VCs adopt a "winner-takes-all" approach that aligns with the inherently stochastic and high-variance nature of intangible investments.

Beyond the tangible–intangible distinction, differences in the stage and scalability of specific intangibles—such as R&D versus customer capital—may imply that VC financing has fundamentally different drivers and outcomes depending on the type of asset. As such, future research could examine how financing shapes the development of knowledge- and customer-related capital, fund performance in these domains, and broader implications for innovation, firm growth, and value creation.

References

Aragoneses, Martin, "The firm life cycle origins of the aggregate investment puzzle," *Available at SSRN 4863038*, 2023.

_ **and Sagar Saxena**, "Industrial Policy via Venture Capital," *Available at SSRN 5316925*, 2025.

Arora, Abhishek and Melissa Dell, "LinkTransformer: A Unified Package for Record Linkage with Transformer Language Models," 2023.

Auclert, Adrien, Hannes Malmberg, Frédéric Martenet, and Matthew Rognlie, "Demographics, wealth, and global imbalances in the twenty-first century," Technical Report, National Bureau of Economic Research 2021.

Baqaee, David and Emmanuel Farhi, "The microeconomic foundations of aggregate production functions," Technical Report, National Bureau of Economic Research 2018.

Belo, Frederico, Yu Li, Juliana Salomao, and Maria Ana Vitorino, "Intangible Capital Around the World," 2024.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend, "The Impact of Venture Capital Monitoring," *Journal of Finance*, 2016, *71* (4), 1591–1622.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen, "Do private equity owned firms have better management practices?," *American Economic Review*, 2015, *105* (5), 442–446.

Crouzet, Nicolas and Janice Eberly, "Rents and intangible capital: A q+ framework," *The Journal of Finance*, 2023, *78* (4), 1873–1916.

_ **,** _ **, Andrea Eisfeldt, and Dimitris Papanikolaou**, "Intangible capital, firm scope, and growth," Technical Report, Working Paper 2025.

Davis, Steven J., John C. Haltiwanger, Kyle Handley, Josh Lerner, Ben Lipsius, and Javier Miranda, "The (Heterogeneous) Economic Effects of Private Equity Buyouts," *Management Science*, 2021, *67* (4), 1904–1923.

Davis, Steven J, John Haltiwanger, Kyle Handley, Ron Jarmin, Josh Lerner, and Javier Miranda, "Private equity, jobs, and productivity," *American Economic Review*, 2014, *104* (12), 3956–3990.

Dell'Ariccia, Giovanni, Dalida Kadyrzhanova, Camelia Minoiu, and Lev Ratnovski, "Bank lending in the knowledge economy," *The Review of Financial Studies*, 2021, *34* (10), 5036–5076.

Falato, Antonio, Dalida Kadyrzhanova, Jae Sim, and Roberto Steri, "Rising intangible capital, shrinking debt capacity, and the US corporate savings glut," *The Journal of Finance*, 2022, *77* (5), 2799–2852.

Gompers, Paul A., "Optimal Investment, Monitoring, and the Staging of Venture Capital," *Journal of Finance*, 1995, *50* (5), 1461–1489.

_ , Will Gornall, Steven N. Kaplan, and Ilya A. Strebulaev, "How Do Venture Capitalists Make Decisions?," *Journal of Financial Economics*, 2020, *135* (1), 169–190.

Gompers, Paul, Steven N. Kaplan, and Vladimir Mukharlyamov, "What do private equity firms say they do?," *Journal of Financial Economics*, 2016, *121* (3), 449–476.

Gonzales-Uribe, Juanita and Cynthia Mei Balloch, "Leverage limits in good and bad times," *Working Paper*, 2021.

González-Uribe, Juanita, "Exchanges of innovation resources inside venture capital portfolios," *Journal of Financial Economics*, 2020, *135* (1), 144–168.

Gutiérrez, Germán and Thomas Philippon, "Investment-less growth: An empirical investigation," Technical Report, National Bureau of Economic Research 2016.

Hall, Bronwyn H. and Josh Lerner, "The Financing of R&D and Innovation," in Bronwyn H. Hall and Nathan Rosenberg, eds., *Handbook of the Economics of Innovation*, Vol. 1, Elsevier, 2010, pp. 609–639.

He, Bianca, "Financing Intangibles," *SSRN Electronic Journal*, 2025.

_ , Lauren I. Mostrom, and Amir Sufi, "Investing in Customer Capital," 2024.

Hellmann, Thomas, "The Allocation of Control Rights in Venture Capital Contracts," *The RAND Journal of Economics*, 1998, *29* (1), 57–76.

_ , Alexander Montag, and Joacim Tåg, "Tolerating Losses for Growth: J-Curves in Venture Capital Investing," IFN Working Paper No. 1500, Research Institute of Industrial Economics (IFN), Stockholm 2024. Accessed via EconStor.

_ and Manju Puri, "The Interaction between Product Market and Financing Strategy: The Role of Venture Capital," *Review of Financial Studies*, 2000, *13* (4), 959–984.

_ and _ , "Venture Capital and the Professionalization of Start-Up Firms: Empirical Evidence," *Journal of Finance*, 2002, *57* (1), 169–197.

Herkenhoff, Kyle F, Josh Lerner, Gordon M Phillips, Francisca Rebelo, and Benjamin Sampson, "Private equity and workers: Modeling and measuring monopsony, implicit contracts, and efficient reallocation," Technical Report, National Bureau of Economic Research 2025.

Jang, Young Soo, Dasol Kim, and Amir Sufi, "Private Credit at Scale: Evidence from US Regulatory Data," *Working Paper*, 2025.

Kaplan, Steven N. and Per Strömberg, "Characteristics, Contracts, and Actions: Evidence from Venture Capitalist Analyses," *The Journal of Finance*, 2004, *59* (5), 2177–2210.

_ **and Per Strömberg**, "Financial Contracting Theory Meets the Real World: An Empirical Analysis of Venture Capital Contracts," *The Review of Economic Studies*, 2003, *70* (2), 281–315.

_ **, Berk A. Sensoy, and Per Strömberg**, "Should Investors Bet on the Jockey or the Horse? Evidence from the Evolution of Firms from Early Business Plans to Public Companies," *Journal of Finance*, 2009, *64* (1), 75–115.

Kortum, Samuel and Josh Lerner, "Assessing the Contribution of Venture Capital to Innovation," *The RAND Journal of Economics*, 2000, *31* (4), 674–692.

Lerner, Josh, "Venture Capitalists and the Oversight of Private Firms," *Journal of Finance*, 1995, *50* (1), 301–318.

_ **and Ramana Nanda**, "Venture Capital's Role in Financing Innovation: What We Know and How Much We Still Need to Learn," *Journal of Economic Perspectives*, 2020, *34* (3), 237–261.

Li, Ye, "Fragile new economy: intangible capital, corporate savings glut, and financial instability," *American Economic Review*, 2025, *115* (4), 1100–1141.

Matray, Adrien, "The local innovation spillovers of listed firms," *Journal of Financial Economics*, 2021, *141* (2), 395–412.

McGrattan, Ellen R and Edward C Prescott, "Unmeasured Investment and the Puzzling US Boom in the 1990s," *American Economic Journal: Macroeconomics*, 2010, *2* (4), 88–123.

Mian, Atif R, Ludwig Straub, and Amir Sufi, "What explains the decline in r*? Rising income inequality versus demographic shifts," *Rising Income Inequality Versus Demographic Shifts (September 22, 2021). University of Chicago, Becker Friedman Institute for Economics Working Paper*, 2021, (2021-104).

Midrigan, Virgiliu and Daniel Yi Xu, "Finance and misallocation: Evidence from plant-level data," *American economic review*, 2014, *104* (2), 422–458.

Ottonello, Pablo and Thomas Winberry, "Capital, ideas, and the costs of financial frictions," Technical Report, National Bureau of Economic Research 2024.

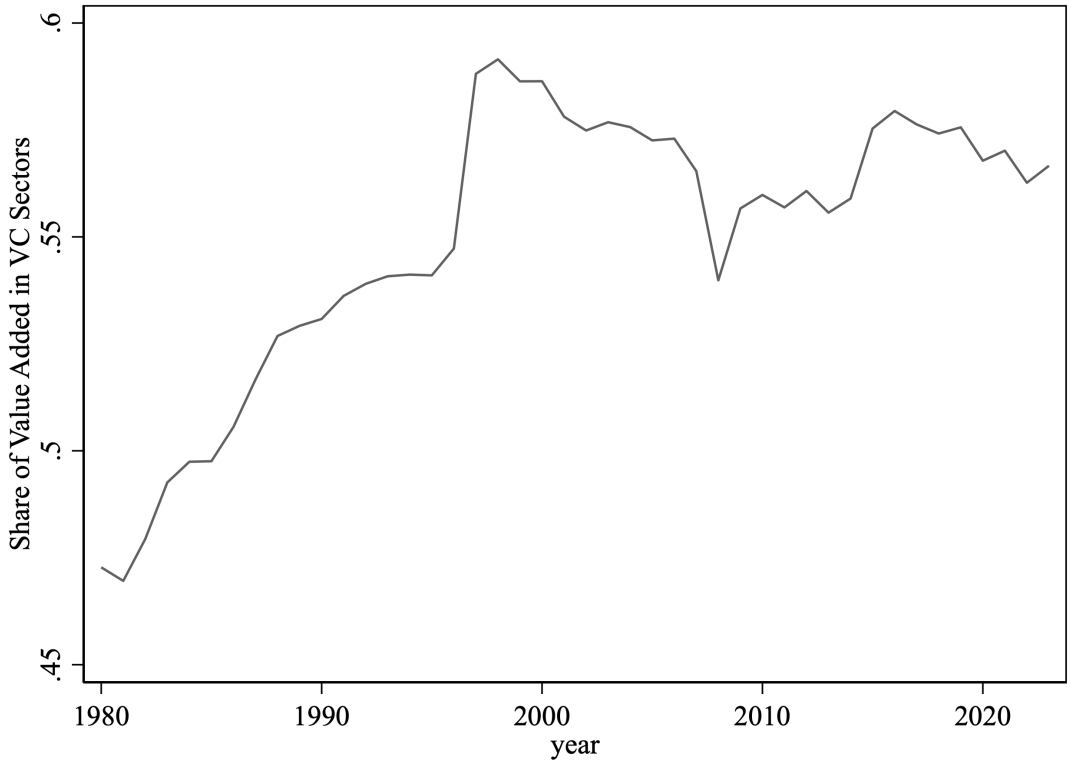
Peters, Ryan H and Lucian A Taylor, "Intangible capital and the investment-q relation," *Journal of Financial Economics*, 2017, *123* (2), 251–272.

Puri, Manju and Rebecca Zarutskie, "On the Life Cycle Dynamics of Venture-Capital- and Non-Venture-Capital-Financed Firms," *Journal of Finance*, 2012, *67* (6), 2247–2293.

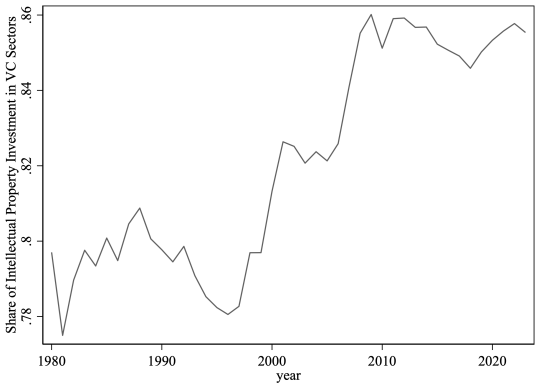
Samuelson, Paul A, "A summing up," *The quarterly journal of economics*, 1966, *80* (4), 568–583.

Winton, Andrew and Vijay Yerramilli, "Entrepreneurial finance: Banks versus venture capital," *Journal of Financial Economics*, 2008, *88* (1), 51–79.

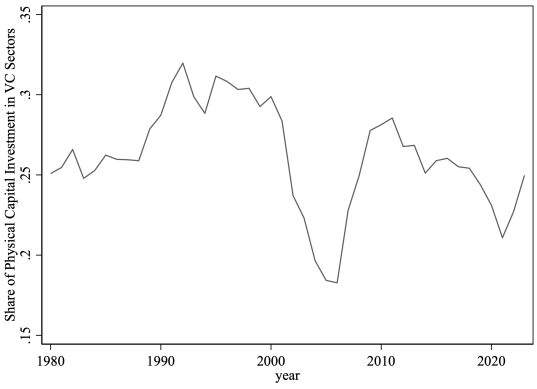
7 Tables and Figures



(a) Value Added & VC

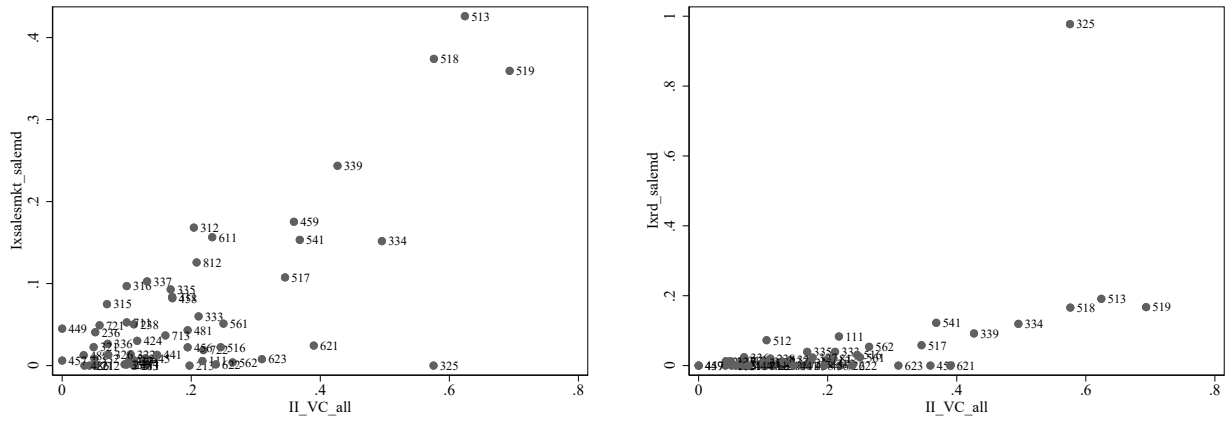


(b) Intellectual Property Investment & VC



(c) Physical Capital Investment & VC

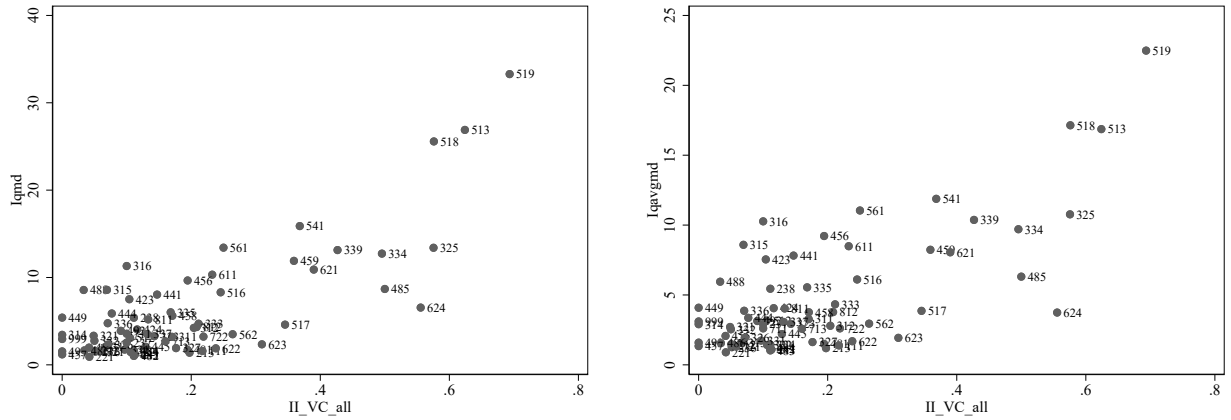
Figure 1: BEA Share of Value Added, Intellectual Property Investment, and Physical Capital Investment Concentrated in Sectors with above-median Share of VC-Backed Firms



(a) Sales & Marketing I/Y vs VC Share (b) Research & Development I/Y vs VC Share

Figure 2: VC presence and intangible investment across industries

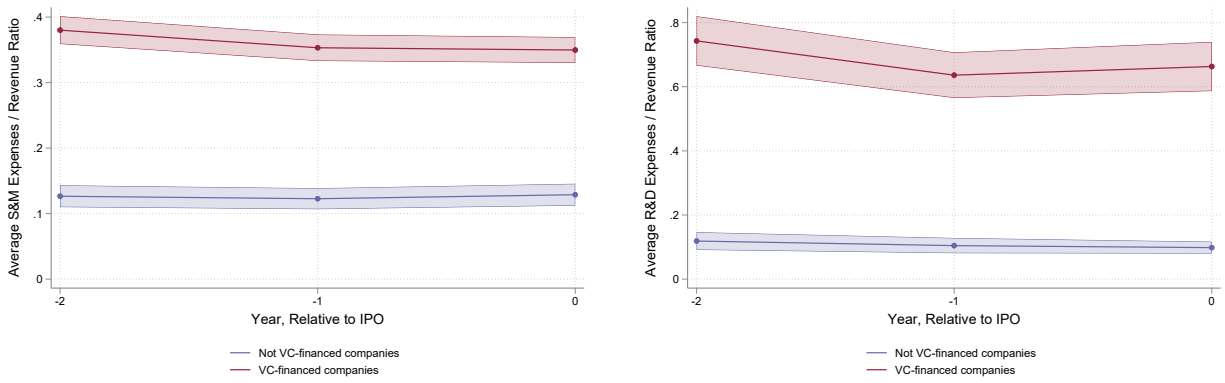
This graph uses data on public firms in the merged PitchBook–Revelio–Compustat sample. S&M/R&D expenses and revenue are from Compustat. Industry is measured at the NAICS 3-digit level.



(a) Median "Q" (b) Average "Q"

Figure 3: VC presence and intangible value "q" across industries

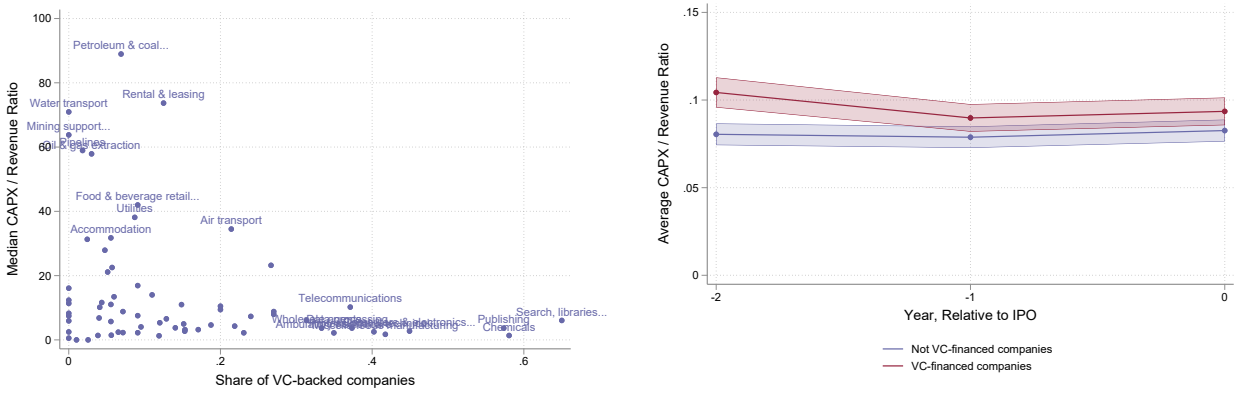
This graph uses data on public firms in the merged PitchBook–Revelio–Compustat sample. "q" is constructed from Compustat data as the market value of the firm's assets, proxied by the market value of equity plus debt net of cash, divided by gross property, plant, and equipment. For building-construction firms, the denominator is expanded to include inventories in addition to gross property, plant, and equipment. Industry is measured at the NAICS 3-digit level.



(a) Sales & Marketing I/Y by VC-backing (b) Research & Development I/Y by VC-backing

Figure 4: VC backing and intangible investment pre-IPO

This graph uses data on public firms in the merged PitchBook–Revelio–Compustat sample. S&M/R&D expenses and revenue are from Compustat. Industry is measured at the NAICS 3-digit level. The confidence intervals are shown at the 95% level.



(a) CAPX / Sale I/Y by VC Share Across Industries (b) CAPX / Sale I/Y by VC-backing pre IPO

Figure 5: VC backing and tangible investment

This graph uses data on public firms in the merged PitchBook–Revelio–Compustat sample. CAPX expenses and revenue are from Compustat. Industry is measured at the NAICS 3-digit level. The confidence intervals are shown at the 95% level.

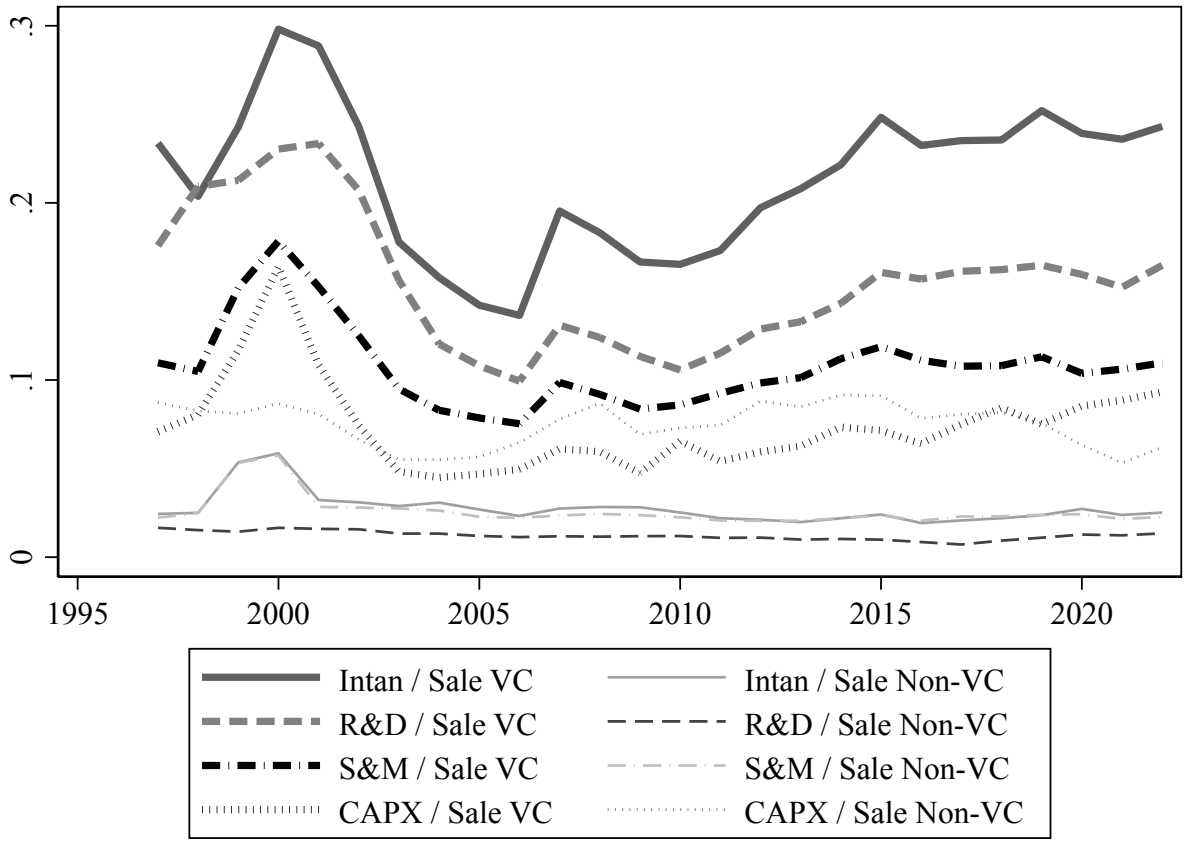


Figure 6: Intangible & tangible investment ratios: VC vs Non-VC backed firms

This graph uses data on all firms in Compustat founded after 1990 and plots average investment ratios by year. Information on VC financing comes from PitchBook. Intangible investment is calculated as the sum of S&M expenditures and R&D expenditures.

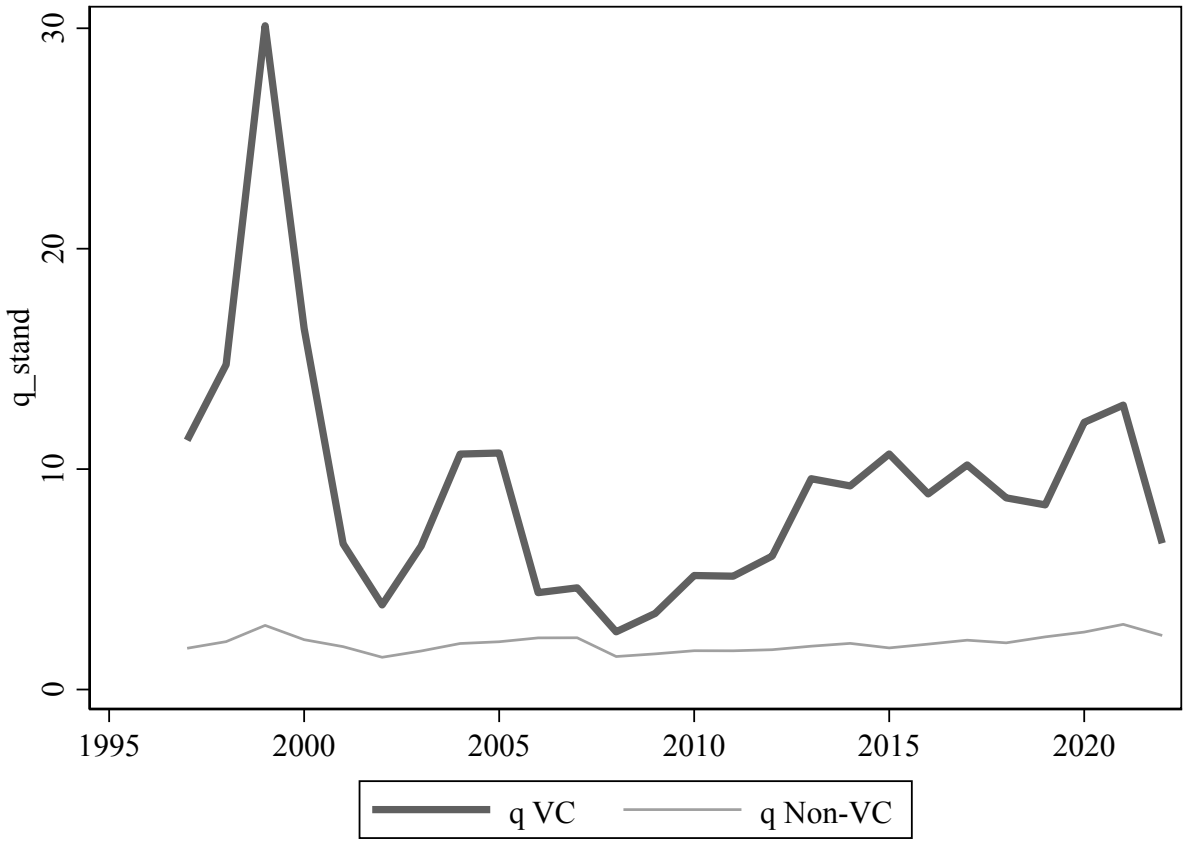


Figure 7: Intangible value "Q": VC vs Non-VC backed firms

This graph uses data on all firms in Compustat founded after 1990 and plots average investment ratios by year. Information on VC financing comes from PitchBook. "q" is constructed from Compustat data as the market value of the firm's assets, proxied by the market value of equity plus debt net of cash, divided by gross property, plant, and equipment. For building-construction firms, the denominator is expanded to include inventories in addition to gross property, plant, and equipment.

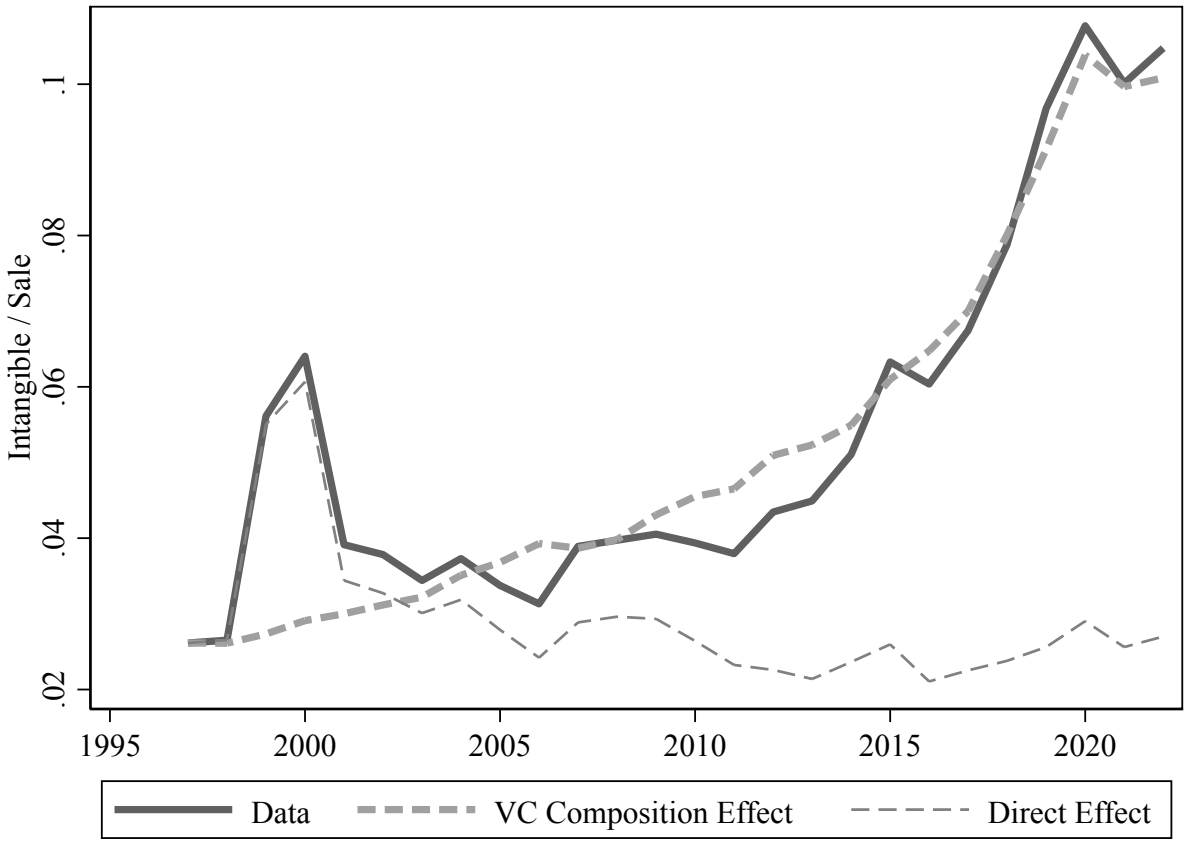


Figure 8: Changes in the VC-Backed Share of Activity and Intangible Investment

This graph uses data on all firms in Compustat founded after 1990. Information on VC financing comes from PitchBook. Intangible investment is calculated as the sum of S&M expenditures and R&D expenditures.

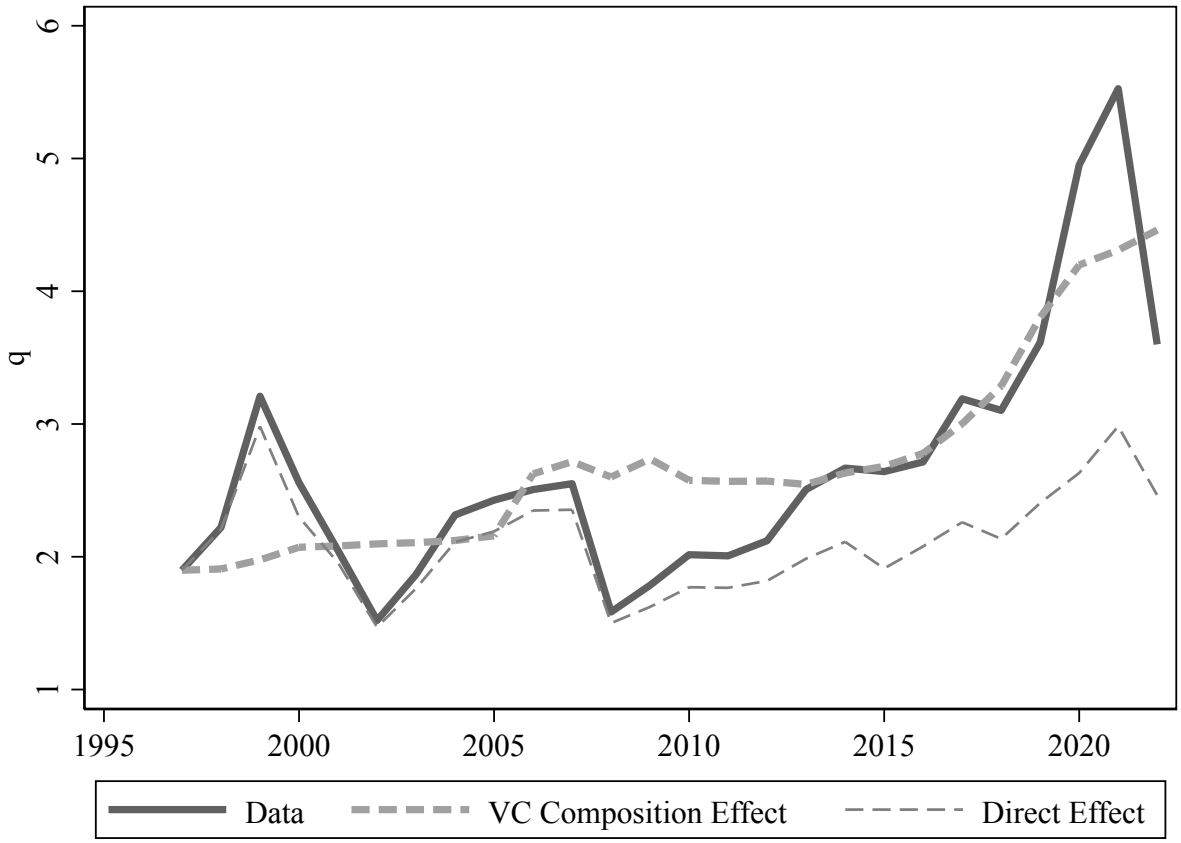


Figure 9: Changes in the VC-Backed Share of Activity and Intangible Value "Q"

This graph uses data on all firms in Compustat founded after 1990. Information on VC financing comes from PitchBook. "q" is constructed from Compustat data as the market value of the firm's assets, proxied by the market value of equity plus debt net of cash, divided by gross property, plant, and equipment. For building-construction firms, the denominator is expanded to include inventories in addition to gross property, plant, and equipment.

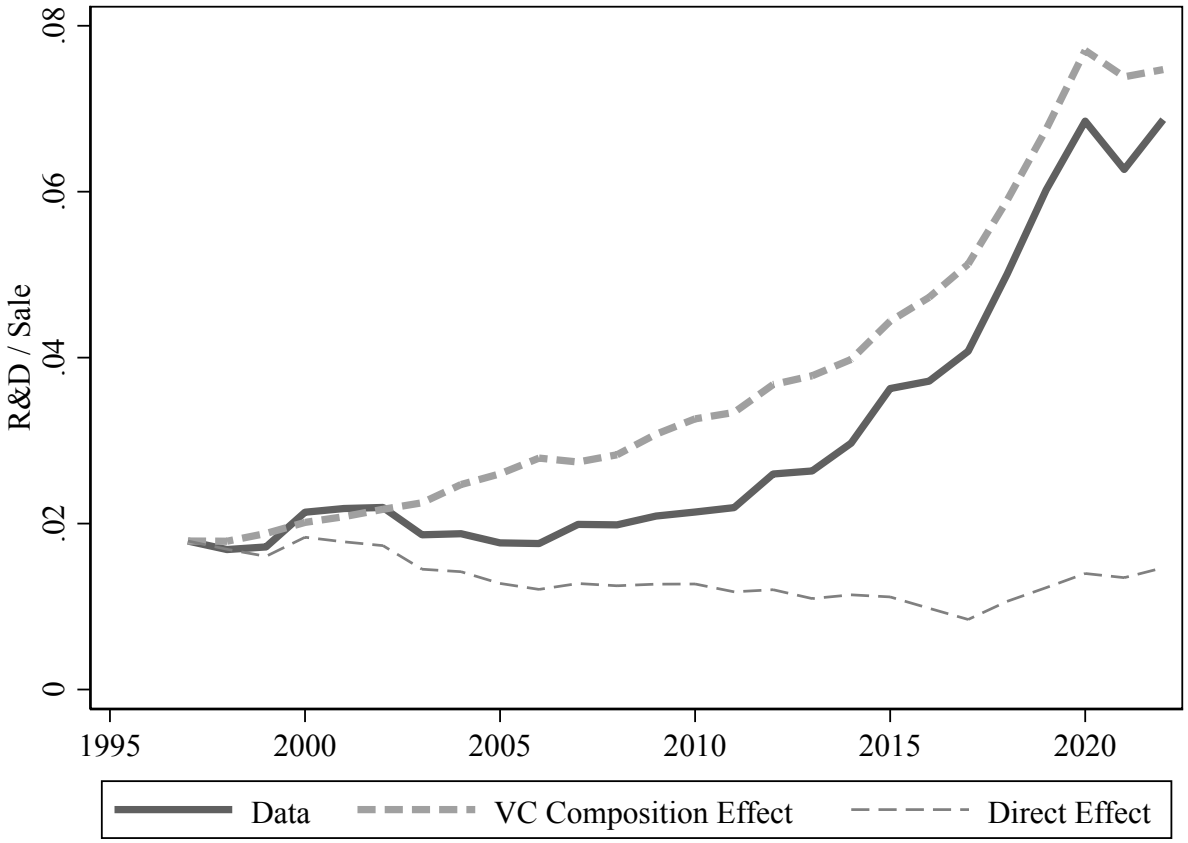


Figure 10: Changes in the VC-Backed Share of Activity and R&D Investment

This graph uses data on all firms in Compustat founded after 1990. Information on VC financing comes from PitchBook.

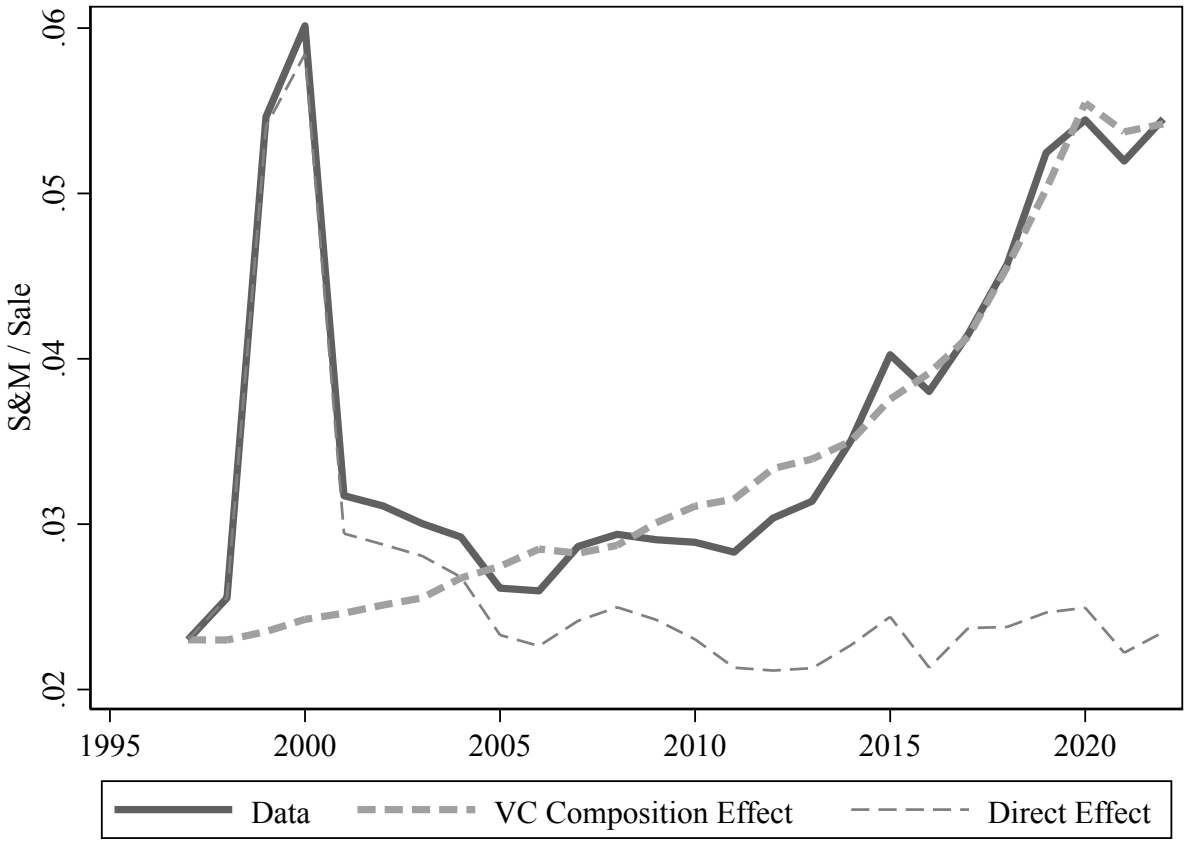


Figure 11: Changes in the VC-Backed Share of Activity and S&M Investment

This graph uses data on all firms in Compustat founded after 1990. Information on VC financing comes from PitchBook.

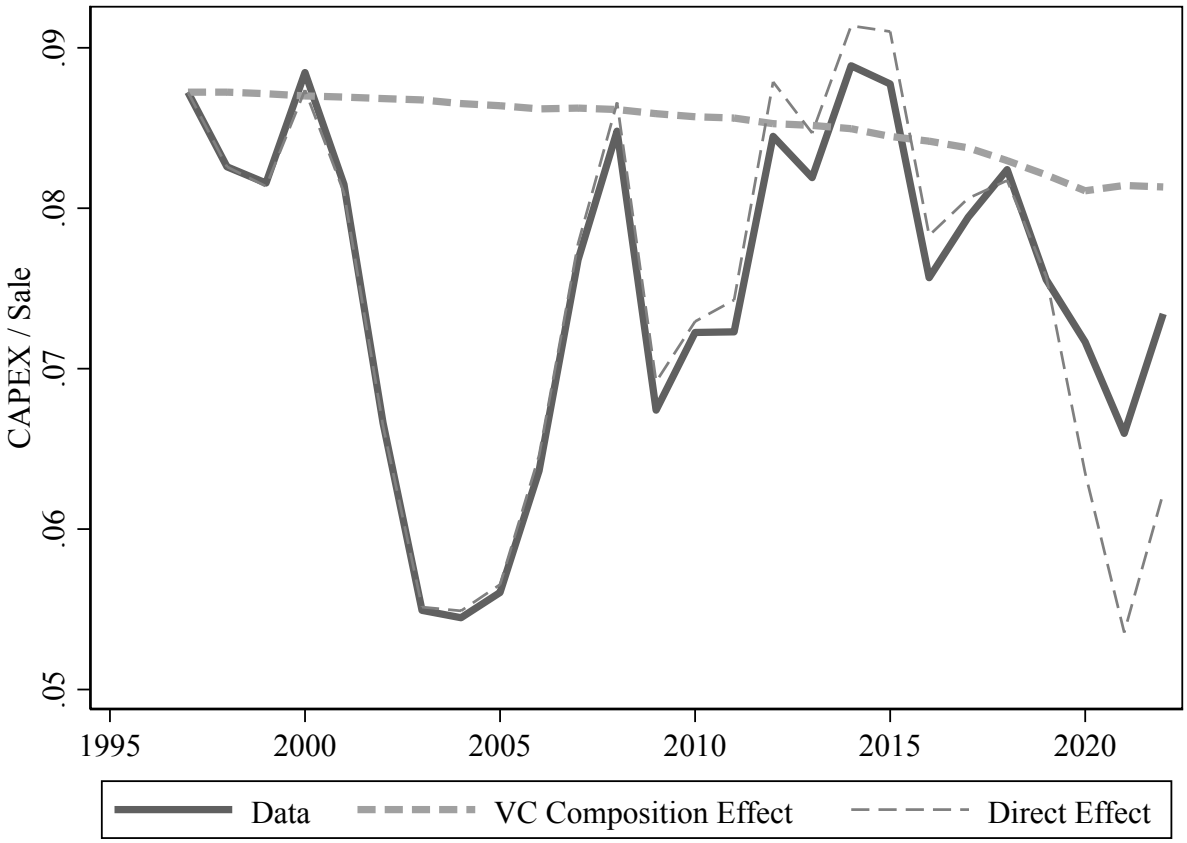


Figure 12: Changes in the VC-Backed Share of Activity and Tangible Capital Investment

This graph uses data on all firms in Compustat founded after 1990. Information on VC financing comes from PitchBook.

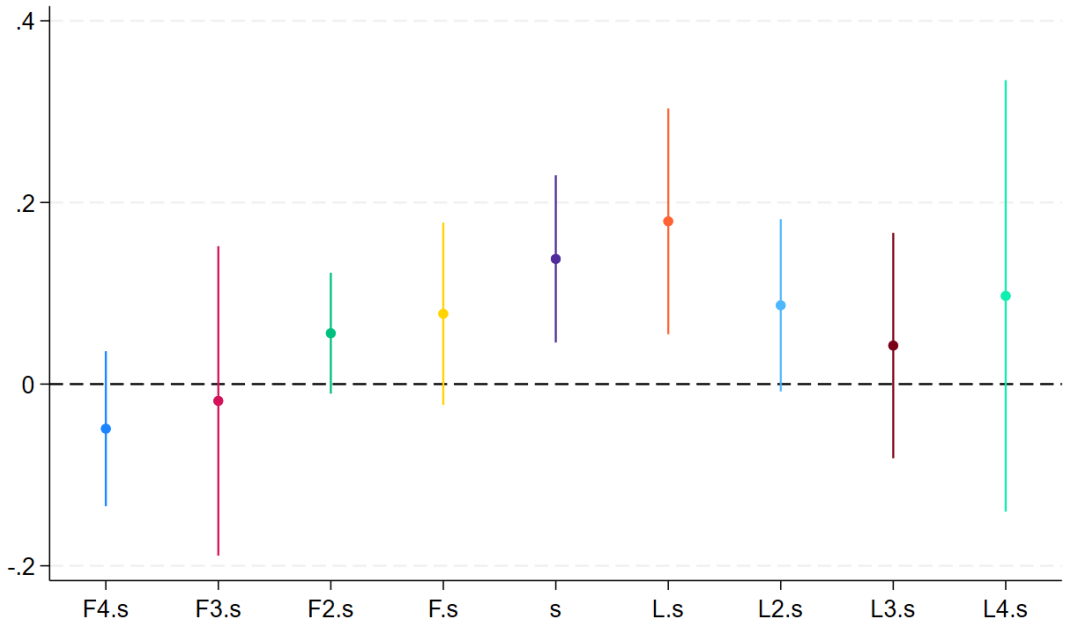


Figure 13: VC deals vs Pension Shock (OLS)

This figure shows the first-stage effects of the pension shock on VC deals. The plotted coefficients are based on the timing of the pension shock (from four years ahead to four years lagged), and the confidence intervals are shown at the 99% level.

Table 1: IV Regressions: Young Firm Employment vs VC Deals (Z: Lagged Pension Exposure)

	(1) VC	(2) Log(Emp)	(3) Log(Emp)	(4) Log(Emp)
Exposure (Lagged)	0.197***			
	(0.0419)			
VC		0.0352	-1.051	0.126**
		(0.107)	(7.437)	(0.0562)
KP F-stat	22.15			
Reg Type	1st Stage	IV	IV	IV
Sample	All	All	Low S&M	High S&M
State-Year FE	Yes	Yes	Yes	Yes
NAICS2-Year FE	Yes	Yes	Yes	Yes
State-NAICS2 FE	Yes	Yes	Yes	Yes
N	9830	9830	2696	5963
R2	0.91	-0.00	-5.33	-0.13

Standard errors in parentheses

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

Table 2: IV Regressions: Young Firm Employment vs Lagged VC Deals (Z: Lagged Pension Exposure)

	(1) L.VC	(2) Log(Emp)	(3) Log(Emp)	(4) Log(Emp)
L.Exposure (Lagged)	0.229***			
	(0.0661)			
L.VC		0.196**	0.215	0.127*
		(0.0827)	(0.606)	(0.0711)
KP F-stat	11.96			
Reg Type	1st Stage	IV	IV	IV
Sample	All	All	Low S&M	High S&M
State-Year FE	Yes	Yes	Yes	Yes
NAICS2-Year FE	Yes	Yes	Yes	Yes
State-NAICS2 FE	Yes	Yes	Yes	Yes
N	9541	9541	2600	5822
R2	0.89	-0.48	-0.48	-0.23

Standard errors in parentheses

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

Table 3: IV Regressions: Old Firm Employment vs VC Deals (Z: Lagged Pension Exposure)

	(1) VC	(2) Log(Emp)	(3) Log(Emp)	(4) Log(Emp)
Exposure (Lagged)	0.197***			
	(0.0414)			
VC		-0.0304	-0.0848	-0.00488
		(0.0415)	(1.477)	(0.0278)
KP F-stat	22.54			
Reg Type	1st Stage	IV	IV	IV
Sample	All	All	Low S&M	High S&M
State-Year FE	Yes	Yes	Yes	Yes
NAICS2-Year FE	Yes	Yes	Yes	Yes
State-NAICS2 FE	Yes	Yes	Yes	Yes
N	9845	9845	2711	5963
R2	0.91	-0.04	-0.42	-0.00

Standard errors in parentheses

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

Table 4: IV Regressions: Old Firm Employment vs Lagged VC Deals (Z: Lagged Pension Exposure)

	(1) L.VC	(2) Log(Emp)	(3) Log(Emp)	(4) Log(Emp)
L.Exposure (Lagged)	0.223***			
	(0.0656)			
L.VC		-0.0532	0.164	0.0135
		(0.0441)	(0.138)	(0.0342)
KP F-stat	11.53			
Reg Type	1st Stage	IV	IV	IV
Sample	All	All	Low S&M	High S&M
State-Year FE	Yes	Yes	Yes	Yes
NAICS2-Year FE	Yes	Yes	Yes	Yes
State-NAICS2 FE	Yes	Yes	Yes	Yes
N	9554	9554	2613	5822
R2	0.89	-0.22	-2.39	-0.01

Standard errors in parentheses

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

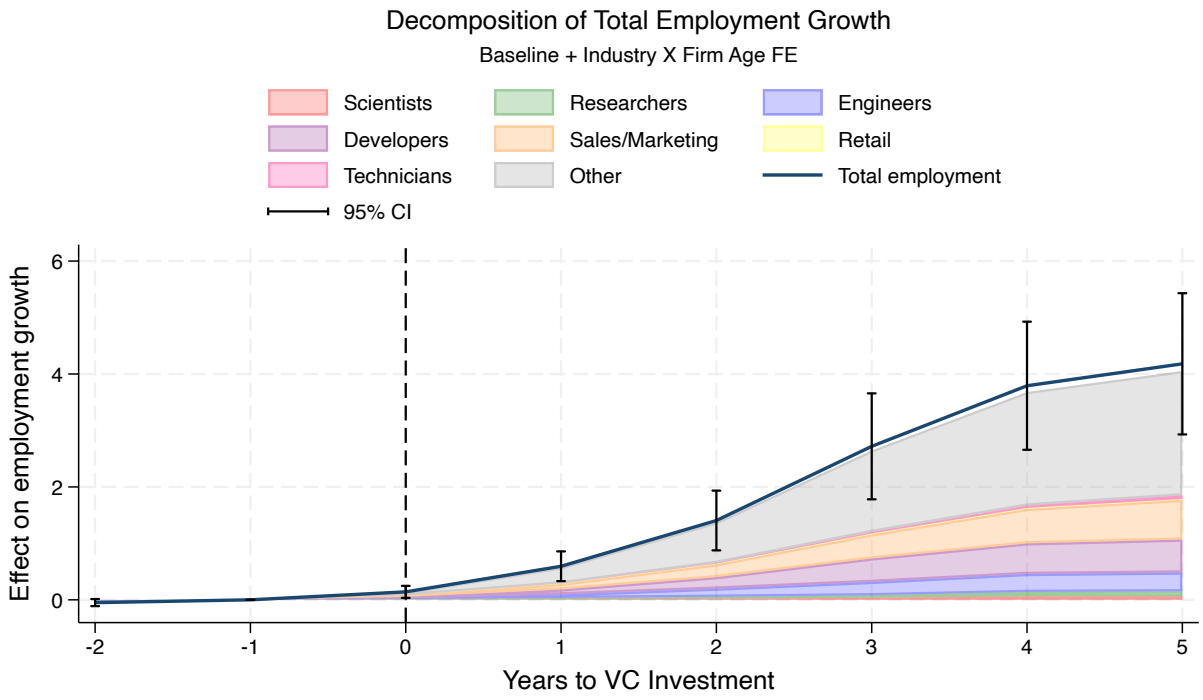


Figure 14: VC Investments Stacked Diff-in-Diff

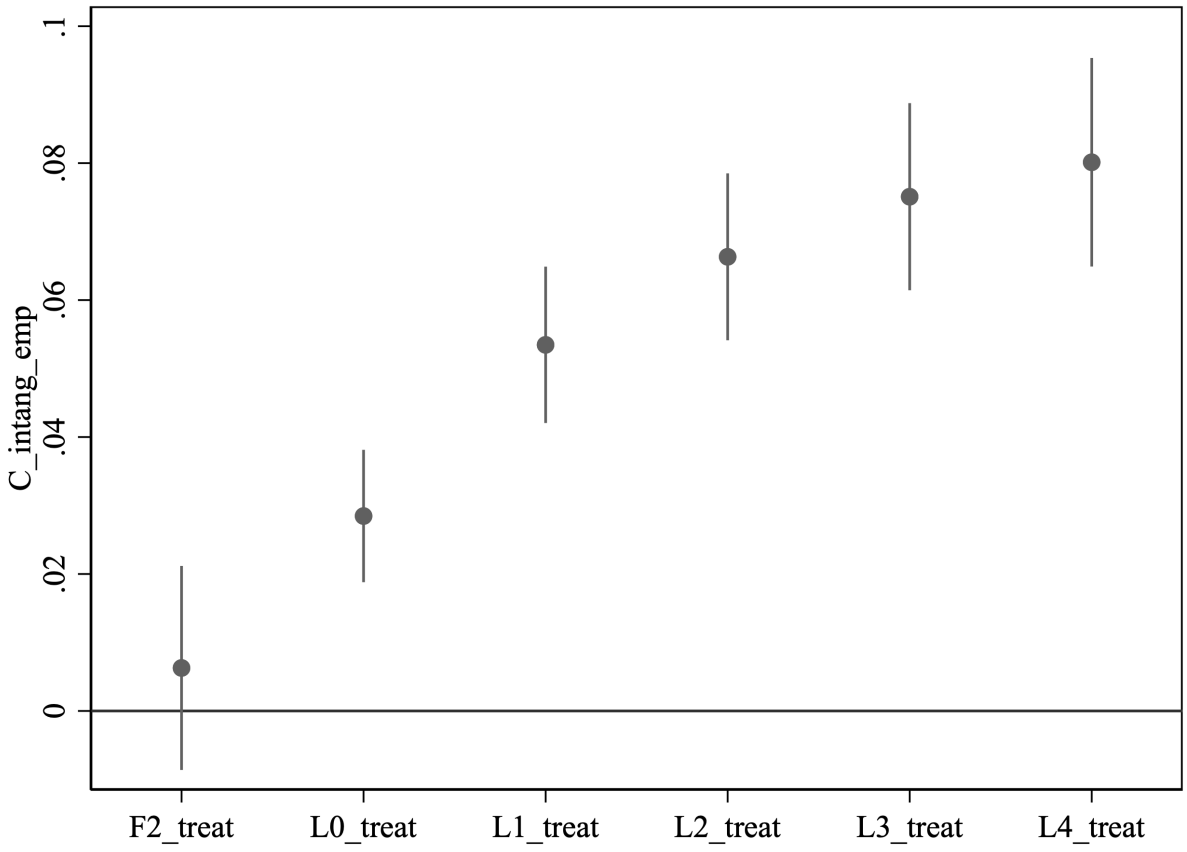


Figure 15: Effect of VC Financing on Intangible Employment Share

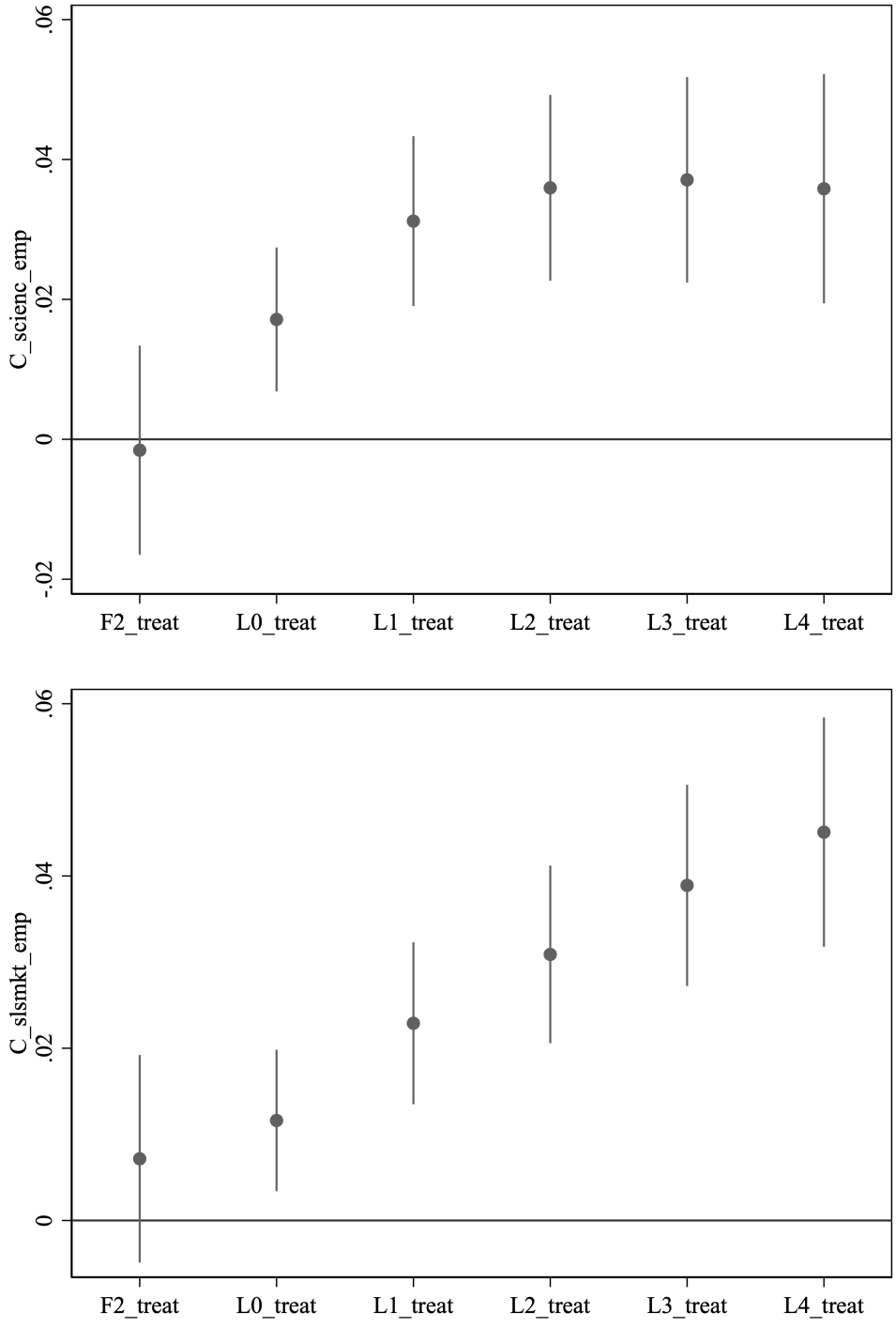


Figure 16: Effect of VC Financing on R&D (top) & S&M (botton) Employment Shares

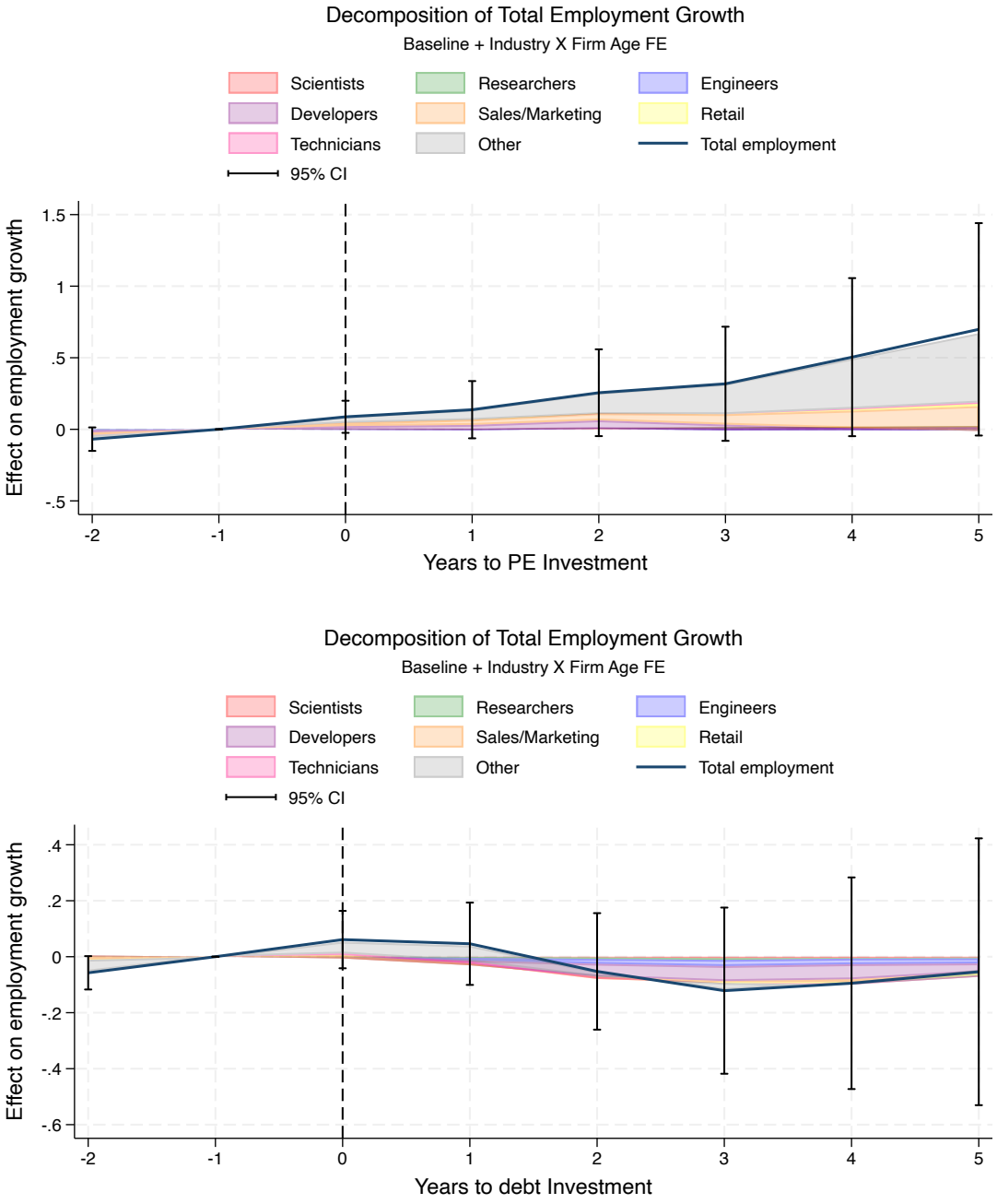


Figure 17: PE and Debt Stacked Diff-in-Diff

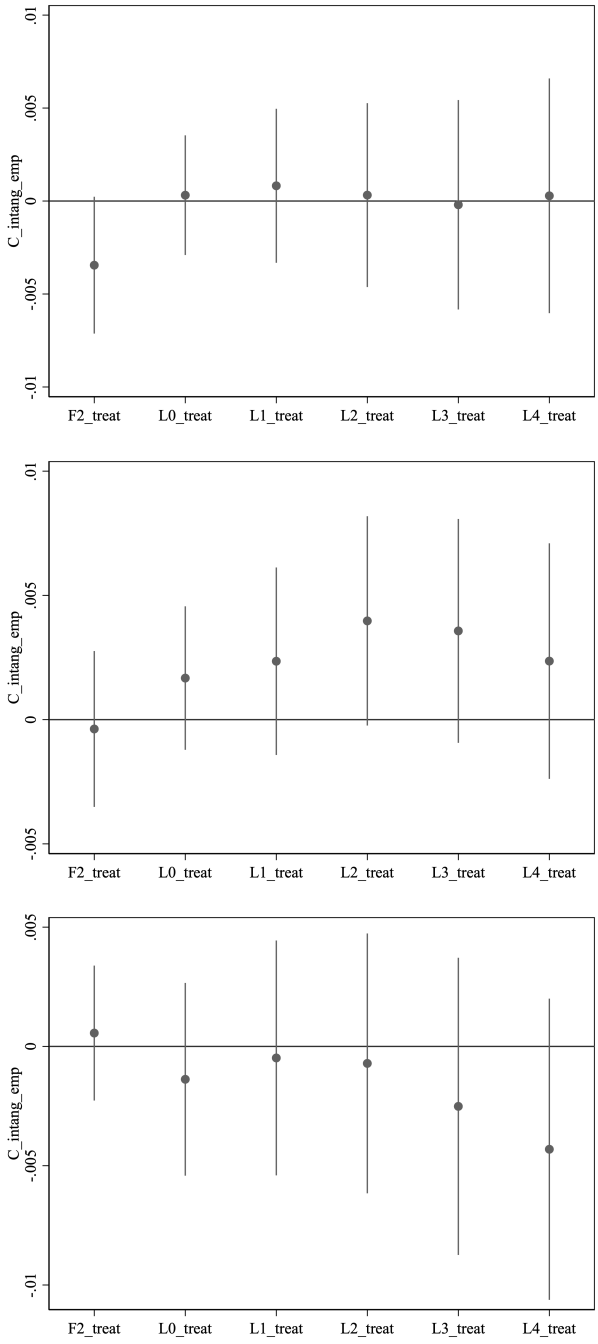
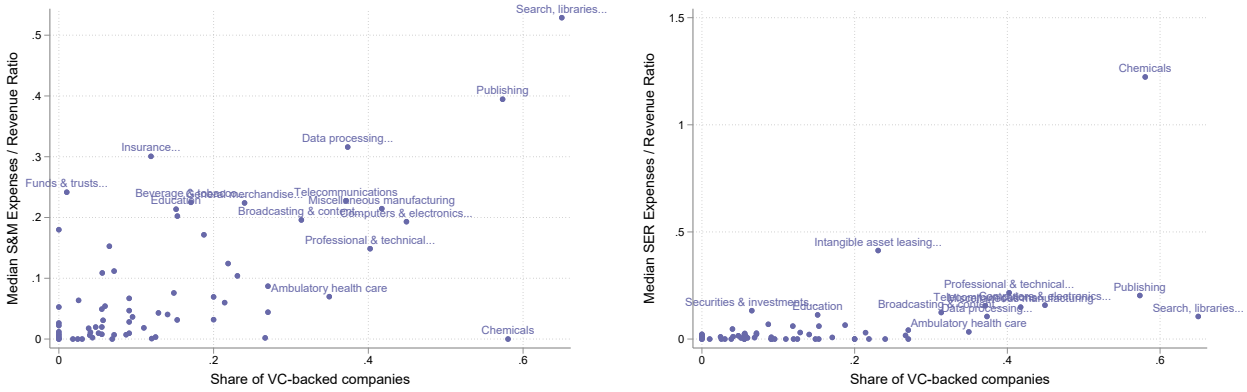


Figure 18: Null effects of PE, debt, and corporate financing on intangible employment shares

Internet Appendix



(a) Sales & Marketing I/Y vs VC Share

(b) Research & Development I/Y vs VC Share

Figure A1: VC Presence and Intangible Investment Across Industries

This graph uses data on public firms in the merged PitchBook–Revelio–Compustat sample. S&M/R&D expenses and revenue are from Compustat. Industry is measured at the NAICS 3-digit level.

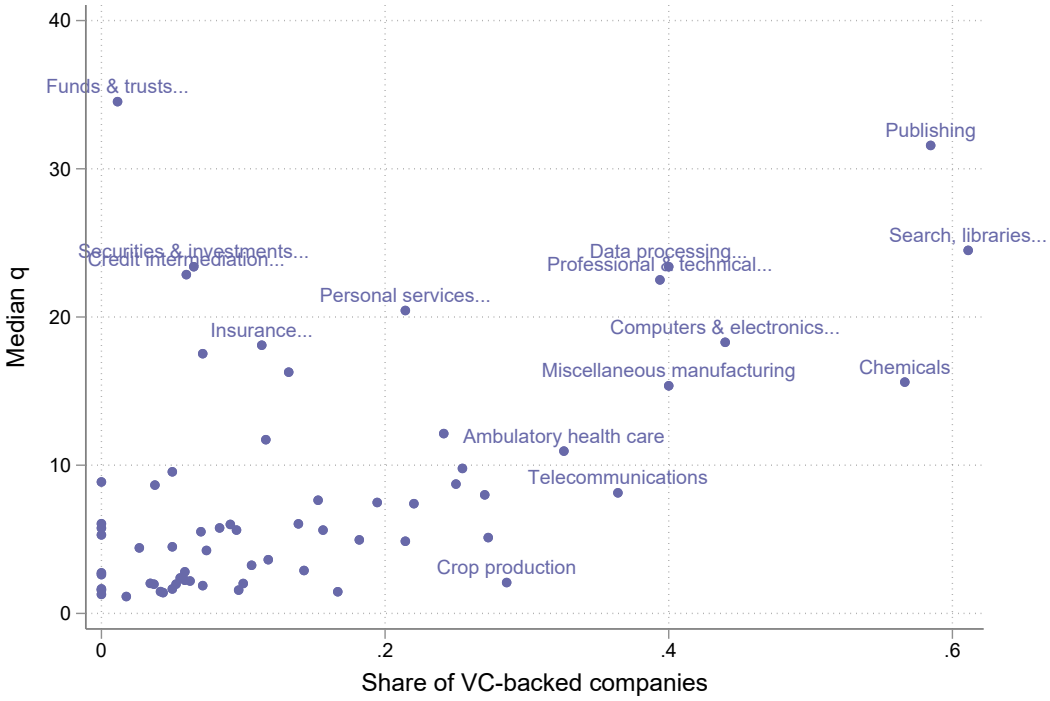
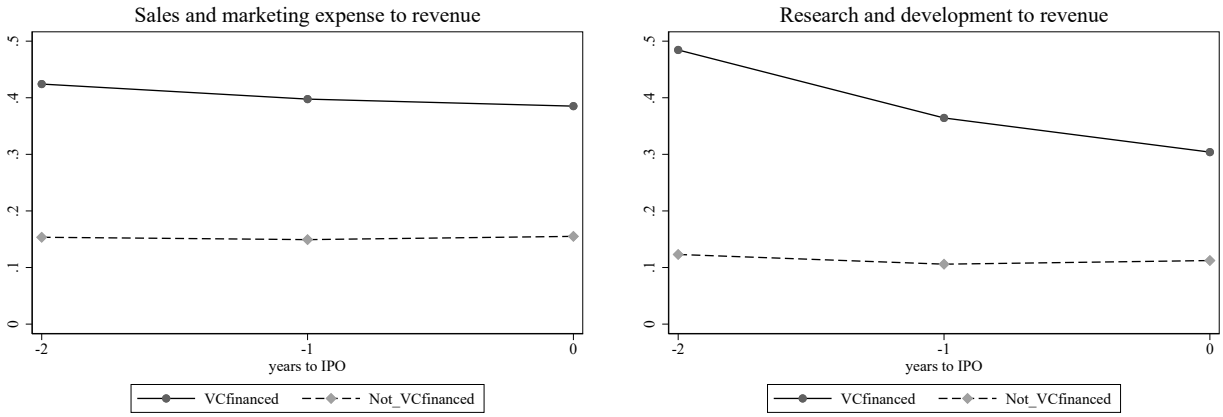


Figure A2: VC presence and intangible value "q" across industries

This graph uses data on public firms in the merged PitchBook–Revelio–Compustat sample. "q" is constructed from Compustat data as the market value of the firm's assets, proxied by the market value of equity plus debt net of cash, divided by gross property, plant, and equipment. For building-construction firms, the denominator is expanded to include inventories in addition to gross property, plant, and equipment. Industry is measured at the NAICS 3-digit level.



(a) Sales & Marketing I/Y by VC-backing (b) Research & Development I/Y by VC-backing

Figure A3: VC backing and intangible investment pre-IPO

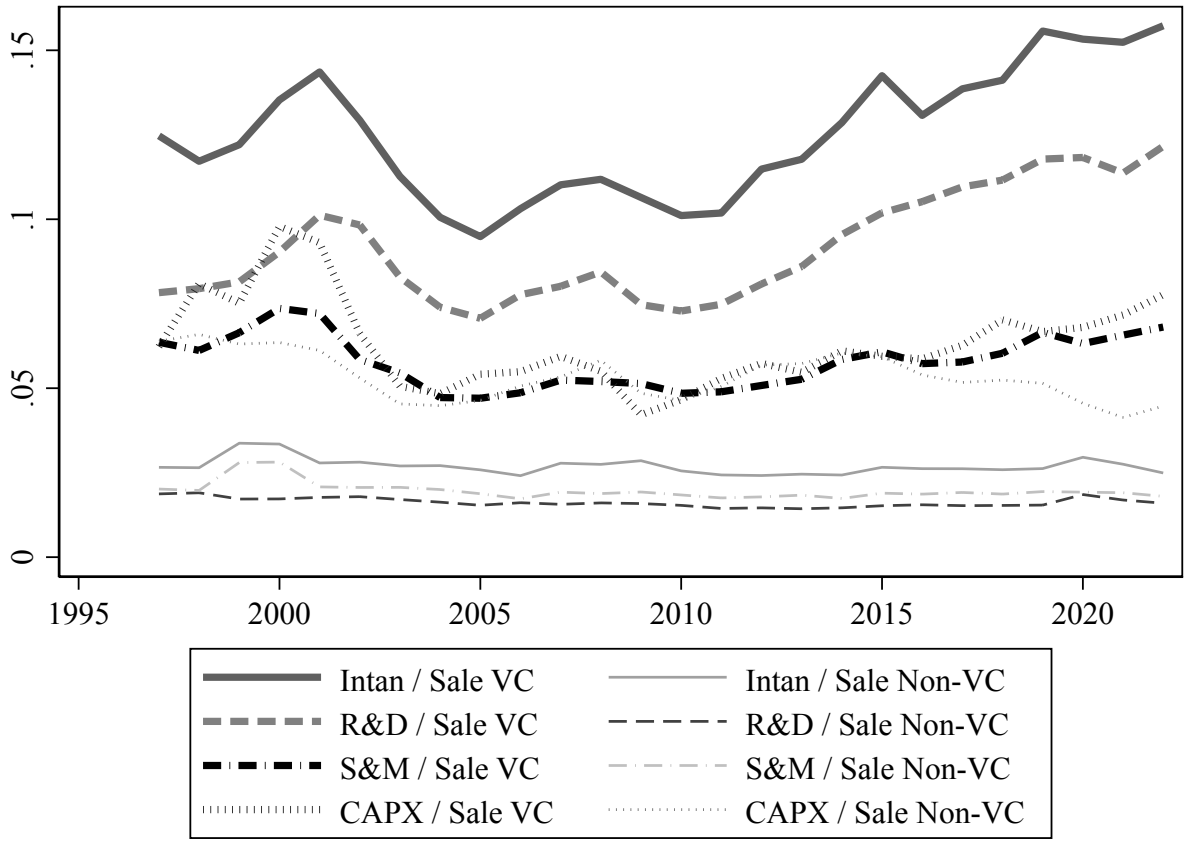


Figure A4: Intangible & tangible investment ratios: VC vs Non-VC backed firms

This graph uses data on all firms in Compustat and plots average investment ratios by year. Information on VC financing comes from PitchBook. Intangible investment is calculated as the sum of S&M expenditures and R&D expenditures.

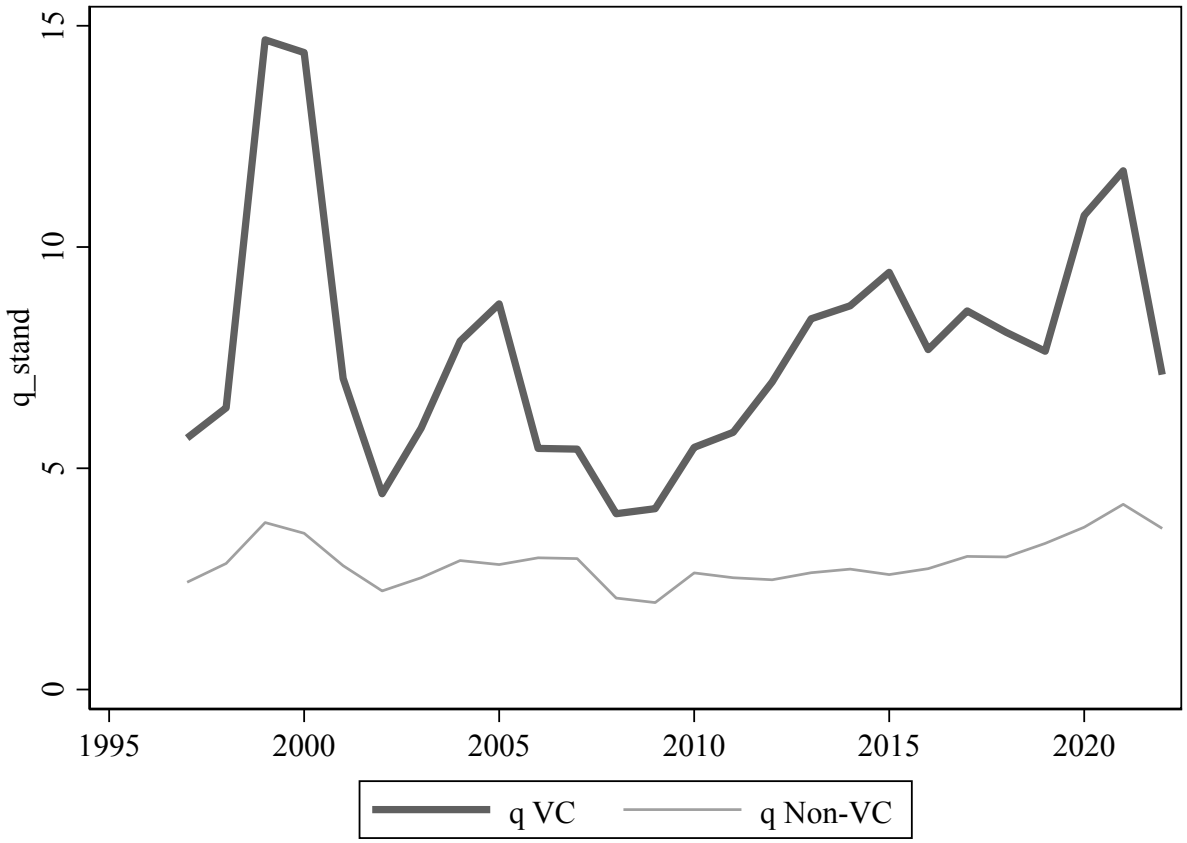


Figure A5: Intangible value "Q": VC vs Non-VC backed firms

This graph uses data on all firms in Compustat and plots average investment ratios by year. Information on VC financing comes from PitchBook. "q" is constructed from Compustat data as the market value of the firm's assets, proxied by the market value of equity plus debt net of cash, divided by gross property, plant, and equipment. For building-construction firms, the denominator is expanded to include inventories in addition to gross property, plant, and equipment.

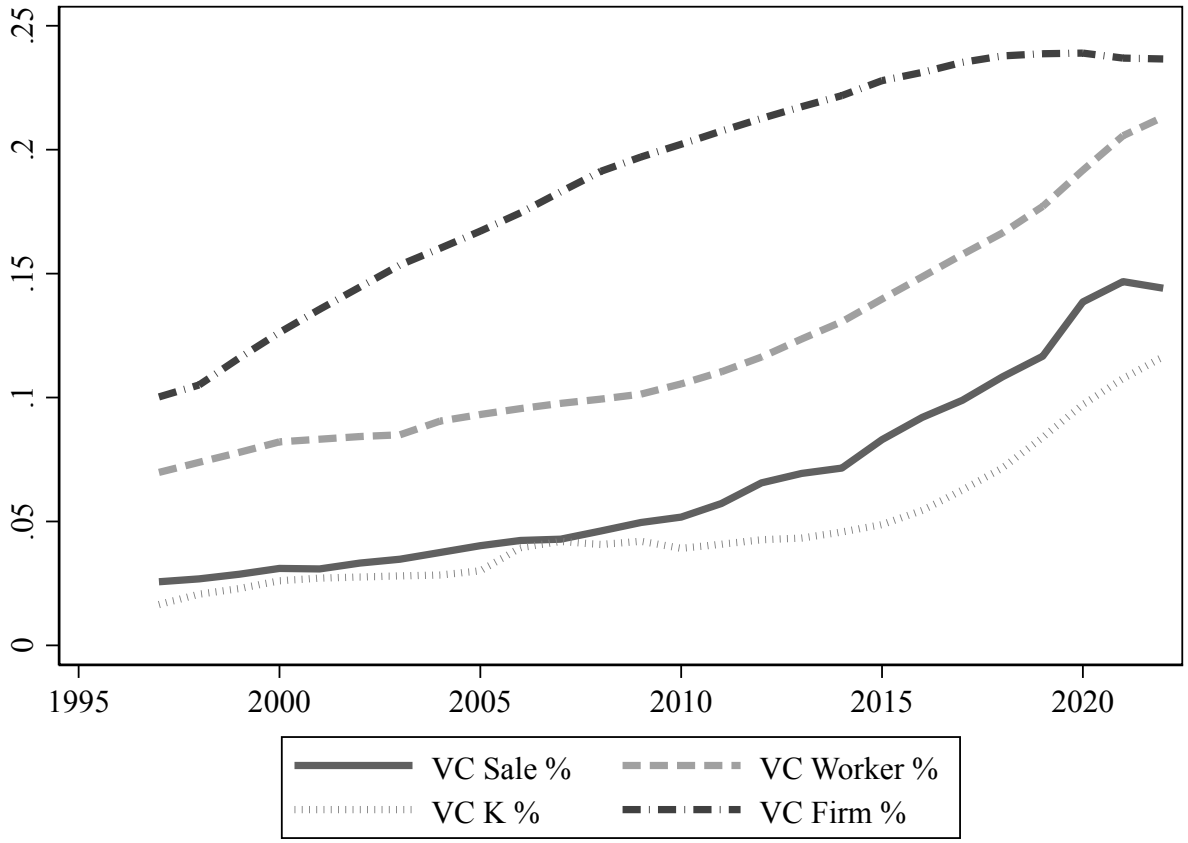


Figure A6: Share of the Economic Activity Concentrated in VC-backed Firms

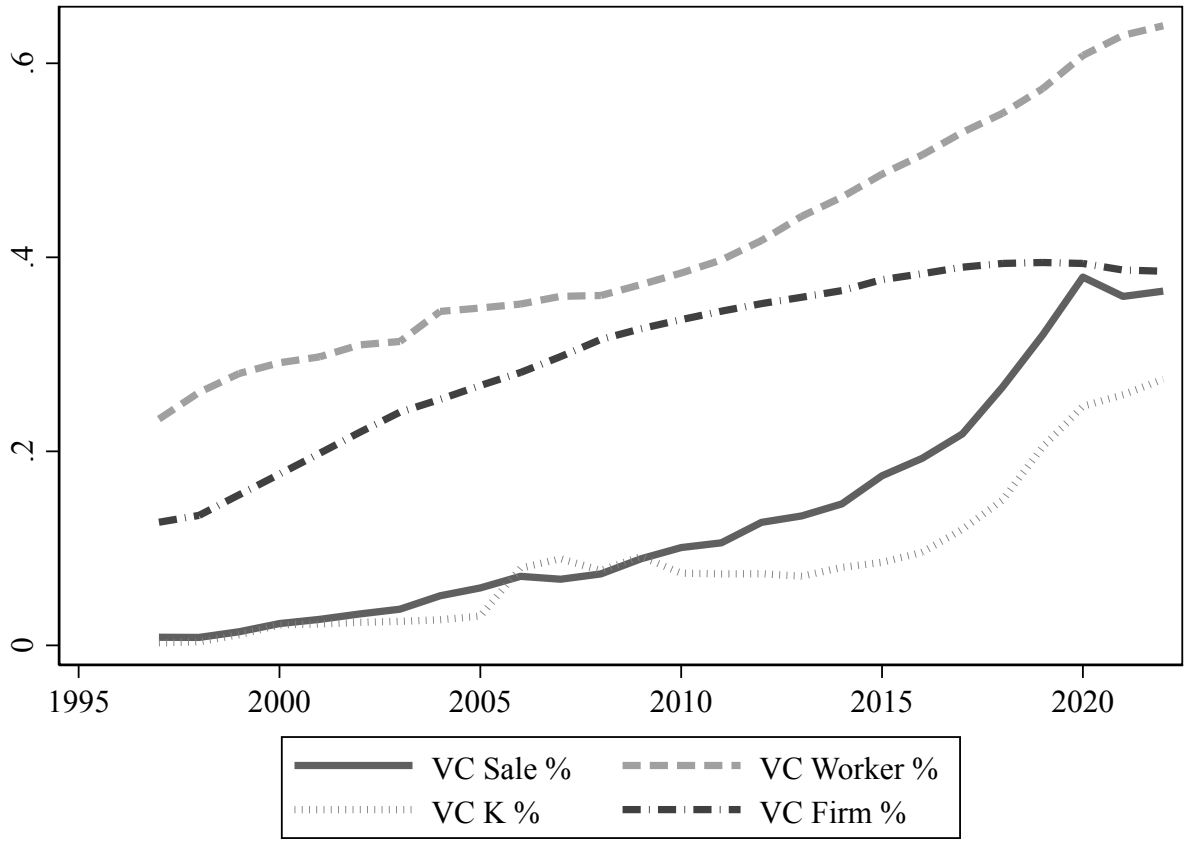


Figure A7: Share of the Economic Activity of Post 1990 Cohorts Concentrated in VC-backed Firms

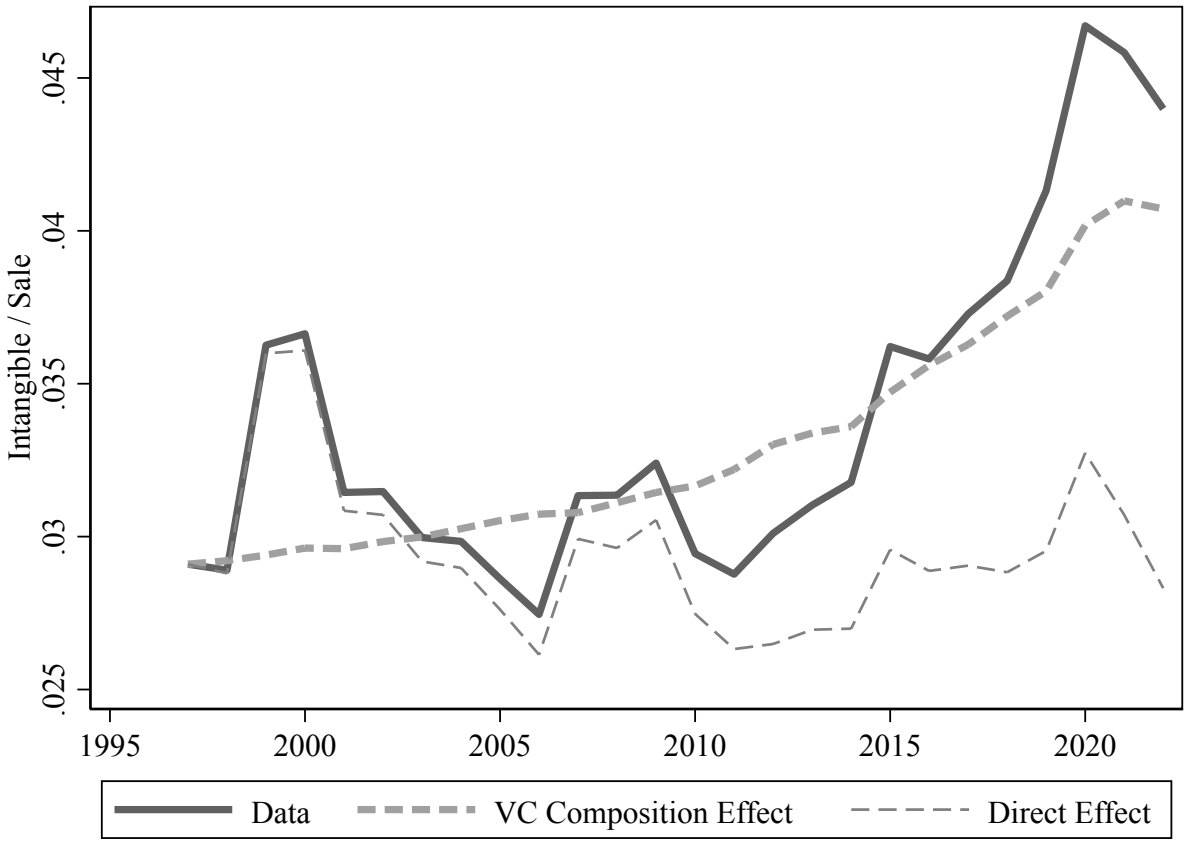


Figure A8: Changes in the VC-Backed Share of Activity and Intangible Intensity I/Y

This graph uses data on all firms in Compustat. Information on VC financing comes from PitchBook. Intangible investment is calculated as the sum of S&M expenditures and R&D expenditures.

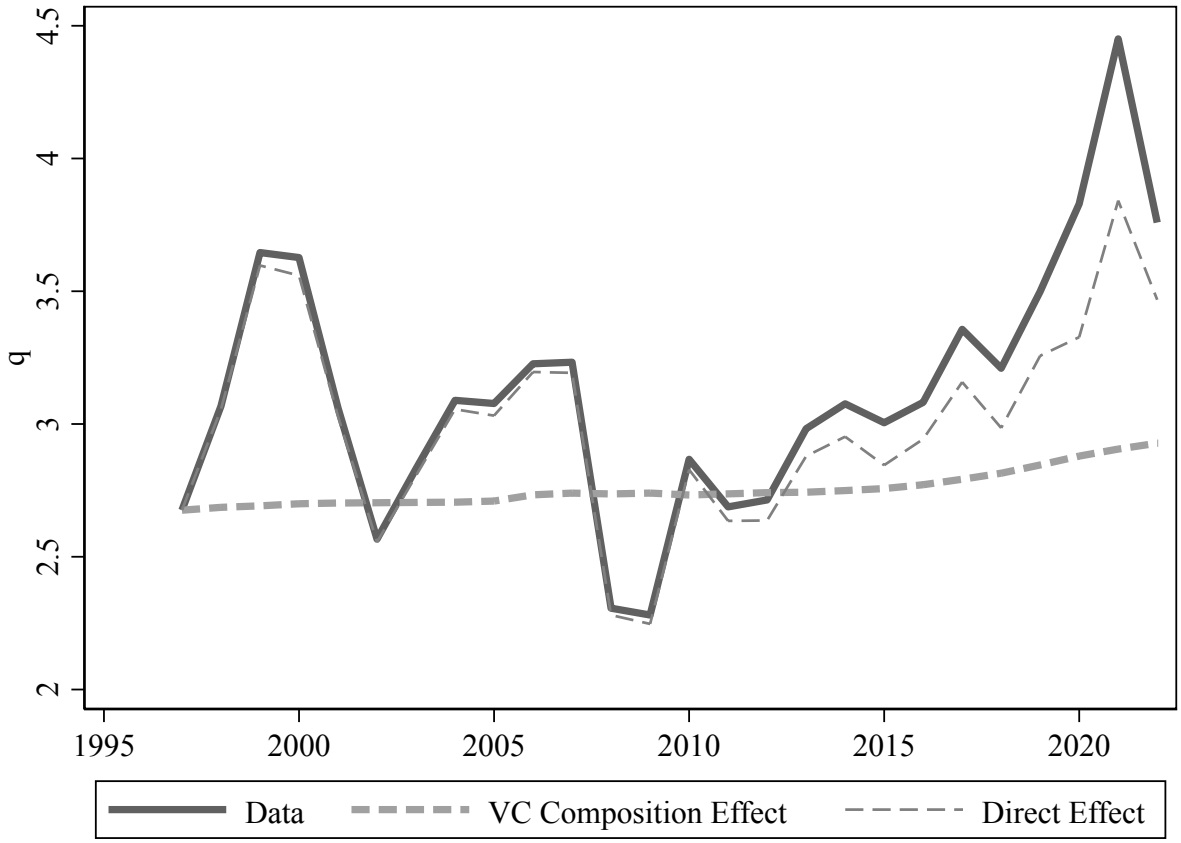


Figure A9: Changes in the VC-Backed Share of Activity and Intangible Value "Q"

This graph uses data on all firms in Compustat. Information on VC financing comes from PitchBook. "q" is constructed from Compustat data as the market value of the firm's assets, proxied by the market value of equity plus debt net of cash, divided by gross property, plant, and equipment. For building-construction firms, the denominator is expanded to include inventories in addition to gross property, plant, and equipment.

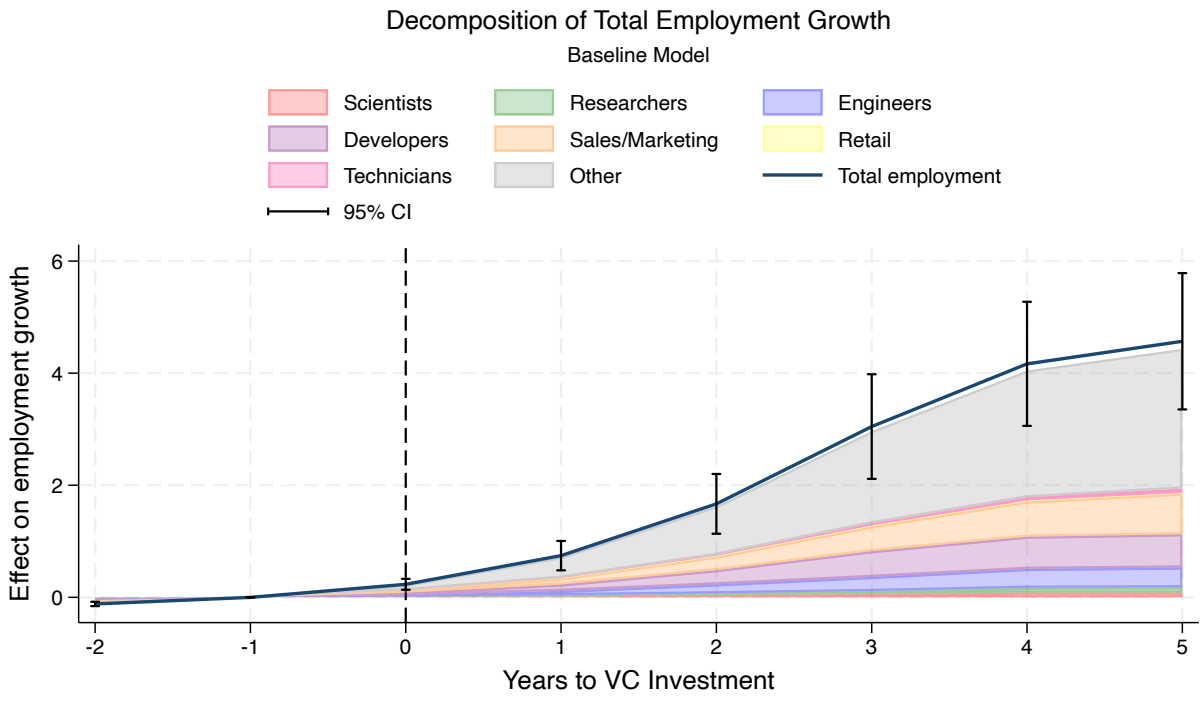


Figure A10: VC Investments Stacked Diff-in-Diff (No Controls)

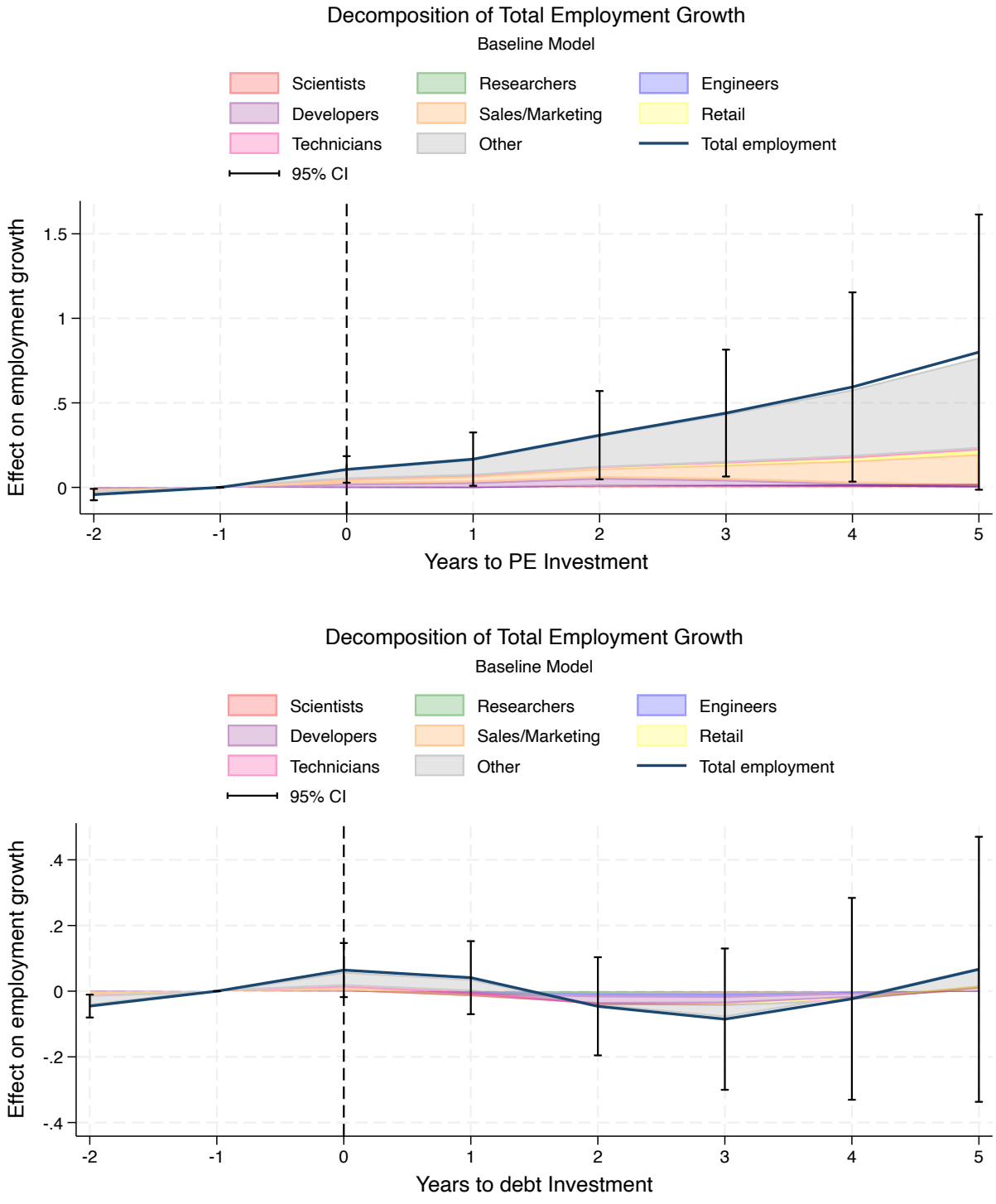


Figure A11: PE and Debt Stacked Diff-in-Diff (No Controls)

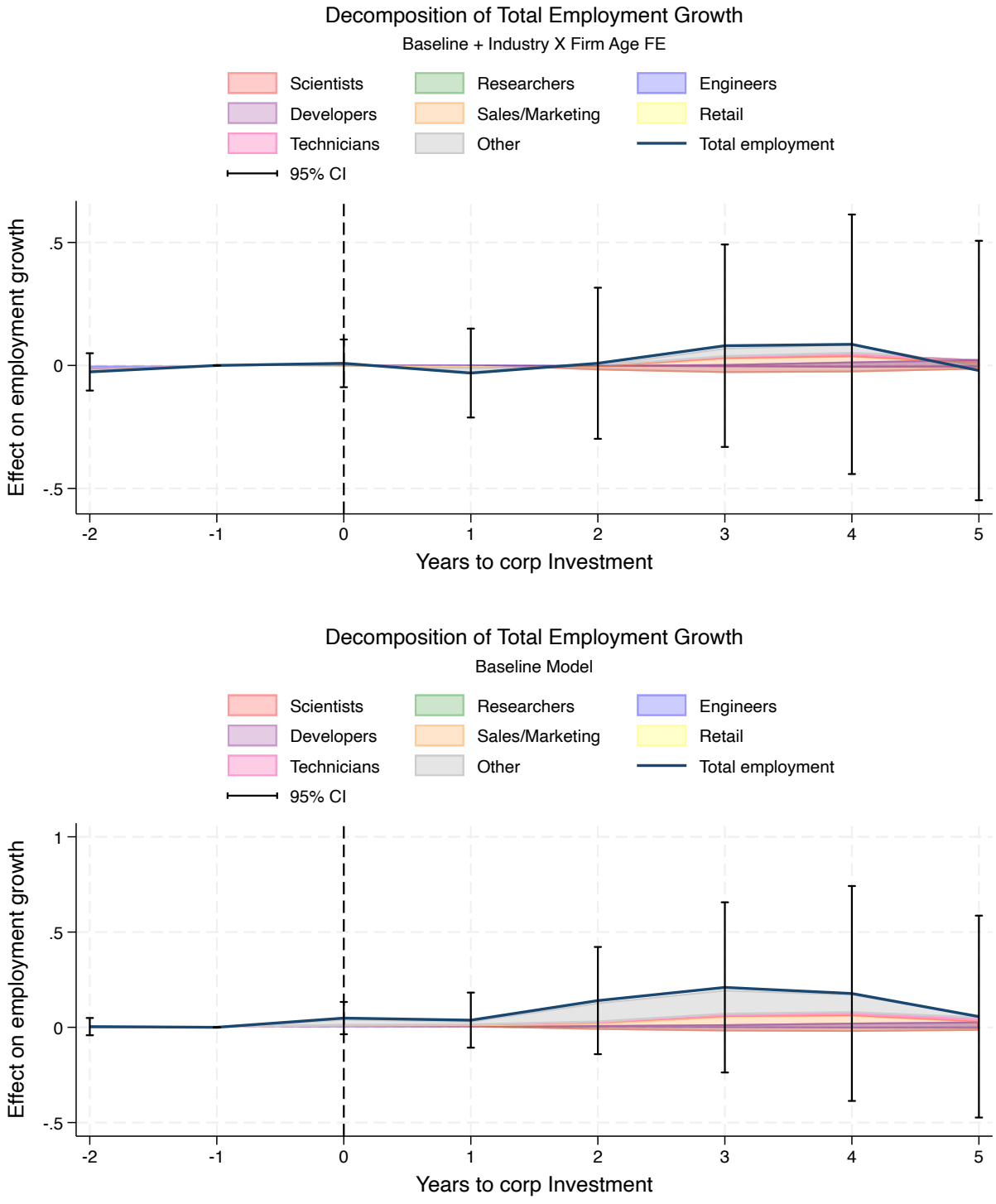


Figure A12: Corporate investments (with and without controls)

	PitchBook Companies	Merged to Revelio	Public Companies
Number of Companies	668,405	500,103	9,477
VC-financed Companies	98,184	87,234	2,379
PE-financed Companies	103,078	83,675	4,010
Average Number of Deals:			
VC Deals (Among VC-financed)	2,23	2,35	3,93
PE Deals (Among PE-financed)	1,32	1,38	2,44
Median Age at the First Deal:			
VC Deals	2	2	2
PE Deals	18	19	18

Merge PitchBook and Revelio

To merge the PitchBook universe of investment deals with employment information from Revelio, we use a two-step procedure:
1) For each U.S. PitchBook company, we first obtain a set of potential candidate companies from Revelio using string and fuzzy matching.
2) Among these potential candidates, we then identify the true match using an LLM.

We construct the pool of potential candidates using three approaches: exact matching on several fields, fuzzy matching within the same state using the full set of available information, and fuzzy matching without restricting matches to the same state. The main idea is that, in the first step, it is more costly to miss the true match than to admit false positives, since false positives can be eliminated in the second step using the LLM.

For the exact string matching, we use the following identifiers:
– Company name + City + ZIP code
– Company legal name + City + ZIP code

– CIK code
– LinkedIn URL
– Website
– Phone number

For the within-state fuzzy matching, we use the LinkTransformer algorithm (Arora and Dell, 2023), which allows us to measure the similarity between PitchBook and Revelio entries using multiple pieces of identifying information simultaneously. Rather than relying on exact agreement in a single field, the method represents each record as an embedding constructed from multiple firm characteristics taken together and then evaluates whether two records refer to the same company based on the similarity of those representations. This allows the procedure to use several identifiers jointly and to recover plausible matches even when company names, locations, or other fields are noisy, incomplete, or formatted differently across the two sources.

For our task, we match companies with LinkTransformer only within the same state, using the following fields to obtain the set of potential matches:
– Company name
– Company legal name
– Website
– Industry information
– City

We also account for inconsistencies in Revelio and PitchBook data entry practices by applying the third approach – less restrictive matching based on:
– Exact name + country
– Exact name only
– Fuzzy name match (using the RapidFuzz Python library) + country, with a blocking rule based on the first three characters of the normalized company name.

We define a match as a true one when all three approaches identify the same candidate, that is, when the exact string match, the highest LinkTransformer similarity match, and the less restrictive match all point to the same company. For observations where the combined candidate pools from

these three approaches still leave more than one potential match, we use the OpenAI GPT–5–mini API. In this step, we provide the same set of identifying information as in the LinkTransformer procedure, while additionally incorporating the textual description fields from both PitchBook and Revelio, and prompt the model to identify the true match for a given PitchBook company from the set of potential Revelio candidates. This pipeline allows us to achieve a matching rate of 74.8%, corresponding to 500,103 matched companies out of 668,405 companies in PitchBook.

Merge PitchBook–Revelio dataset and Compustat

We then merge the Revelio dataset with the Compustat sample of public companies in order to observe information on intangible investment. To do so, we use the following company identifiers available in Revelio/PitchBook:

– Company name
– Company ticker
– CIK code
– GVKEY
– EIN
– CUSIP

Using exact string matches on any of the identifiers listed above, we obtain an n:1 match between Compustat and Revelio. Our PitchBook–Revelio match is also n:1. For example, several investment funds of a single investor may be listed as separate public companies in Compustat and as separate companies in PitchBook, while still being recorded as a single company in Revelio. As a result, at this stage we obtain an n:n match between PitchBook and Compustat. A crucial prerequisite for the subsequent analysis is the accurate identification of whether a public company was VC- or PE-financed before going public. To achieve this and avoid double counting, we further deduplicate the match so that each PitchBook company is linked to a single company in Compustat. Specifically, if a PitchBook company has a recorded ticker or CIK code, we require it to match the corresponding identifier in Compustat, since in the previous step several CIK codes may have been associated with a given Revelio company. For companies without a recorded ticker or CIK code, we retain, for a given Compustat GVKEY, the entry with the smallest time difference between the IPO year recorded in Compustat and the year of the IPO deal recorded in PitchBook; we then drop the en-

try if this difference exceeds two years, allowing for minor inconsistencies in the recorded IPO date.

After these cleaning steps, we drop all remaining entries for which ambiguity cannot be resolved and a 1:1 match between PitchBook and Compustat cannot be established. This merging algorithm is intentionally restrictive, enabling us to construct an accurate flag for VC- and PE-financed companies while still achieving a matching rate of 82% and obtaining a matched sample of 9,477 public companies.