Public Pension Funds and Risk-Taking in Venture Capital

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Abstract

Public pension fund capital in venture capital flows disproportionately toward less risky investments. Venture capital funds with public pension fund investors target opportunities exhibiting higher exit probability but potentially lower returns. General partners manage these funds more conservatively than their other funds with identical investment focuses. Public pension funds slightly prefer later-stage focused funds, with allocations primarily driven by GP size and prior relationships. These findings suggest GPs cater to their limited partners' risk preferences. Pension characteristics such as asset size, funding ratio, and past returns play a limited role in explaining investment patterns and allocation decisions.

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Over recent decades, public pension funds have significantly increased their investments in alternative assets, including venture capital.[1] While researchers have examined the motivations behind this shift and its implications for pension funds, few studies have explored how these institutional investors impact the venture capital industry itself.[2]

The lack of research is particularly puzzling, especially considering that public pension funds are among the largest investors in venture capital while operating with financial goals that differ from other venture capital investors (Hochberg and Rauh (2013)). The significant influx of capital from these institutional actors likely shapes investment flows within the venture capital ecosystem, influencing capital allocation across venture funds and the strategic approaches subsequently adopted by venture capitalists.

Typical risk-return profiles of venture capital investments present distinctive challenges for public pension funds compared to other investor categories. State and local retirement systems predominantly operate defined benefit schemes. The robust contractual and legal frameworks governing public pension benefits effectively render these obligations virtually risk-free liabilities with certainty of payment (Brown and Wilcox (2009)). This guaranteed-payment structure stands in stark contrast to the overall characteristics of venture capital returns, which exhibit significant uncertainty and volatility (Cochrane (2005), Kerr, Nanda, and Rhodes-Kropf (2014)).

The structure of financial liabilities, coupled with the societal importance of public pensions, fundamentally shapes the utility function of public pension funds. During periods of investment under-performance, public pension funds face heightened financial pressures as they must fulfill their defined benefit obligations despite experiencing significant negative returns. Conversely, their predetermined benefit obligations effectively cap the advantages they can derive from exceptionally high investment returns. This creates a highly concave utility function, resulting in a lower risk tolerance among public pension funds relative to other venture capital investors.

The central hypothesis of this paper is that capital from public pension funds flows systematically toward lower-risk investments within the venture capital industry. However, it remains an

[1] State and local pension funds significantly expanded their holdings in alternative investments—including private equity, hedge funds, real estate, and commodities—with allocations growing from 9 percent in 2005 to 24 percent in 2015. (Aubry, Chen, and Munnell (2017)).

[2] Some views on this trend attribute the shift to pressures from underfunded goals (Pennacchi and Rastad (2011), Mohan and Zhang (2014), Lu et al. (2019)), the desire to achieve specific return targets (Andonov, Bauer, and Cremers (2017)), and a changing belief in the risk-reward profiles of alternative investments (Begenau, Liang, and Siriwardane (2023)).

empirical question whether metrics exist that can meaningfully differentiate investment opportunities with low risk and predictable outcomes from other opportunities in the venture capital domain. Equally significant is identifying the specific mechanisms through which public pension fund capital is potentially directed toward these more conservative investment opportunities.

This paper identifies specific startup characteristics associated with higher ex-ante probability of exit, often corresponding with high valuations at the time of investment—including technological proximity to public firms, patent portfolio size, and development stage. Venture capital funds invested by public pension funds disproportionately target investments exhibiting these exit-oriented characteristics. These funds achieve higher exit rates, though potentially at lower returns. General Partners (GPs), who serve as fund managers, operate their funds with public pension fund capital more conservatively than their other funds with the same investment focuses. Public pension funds also demonstrate a preference for funds focused on later-stage startups. However, established relationships with GPs and GP size exert greater influence on their investment decisions than these risk-related characteristics.

The findings suggest that GPs strategically cater to public pension funds' risk preferences. This conclusion aligns with the broader dynamics of the venture capital market, where limited partners (LPs)—investors who provide capital to venture funds—function not merely as current capital providers; they are potential capital sources for follow-on funds, and reputation channels.

The venture capital sector inherently involves long-term, substantial commitments within opaque and illiquid markets, creating significant search costs for identifying appropriate VCs (Duffie, Gârleanu, and Pedersen (2007)). Once investors become LPs in a VC fund, information asymmetries between them and the GP managing the fund decrease substantially. Consequently, GPs who successfully meet investor expectations position themselves favorably for contributions to subsequent funds. Public pension funds, with their considerable asset base, represent particularly valuable repeat investors for venture capital firms.

Furthermore, in this opaque market environment, reputation plays a pivotal role in VC success (Gompers and Lerner (1999), Nahata (2008)) and a VC's current investors often serve as critical information sources for other potential investors. Therefore, successfully meeting the needs of public pension funds may lead to increased investment from other public pension funds with similar investment objectives.

Given these dynamics, the catering behavior of VCs toward public pension funds is a plausible explanation for the findings. Importantly, this pattern carries broader implications for the venture capital industry, particularly regarding its potential to invite investor categories that exhibit lower risk tolerance than conventional VC investors.

This study begins by examining three startup-specific metrics in terms of their relationship with exit outcomes in five years. First, startups' technological relatedness to public companies predicts exit via acquisitions. Controlling for year-sector fixed effects, a standard-deviation increase in the measure of the technological proximity to public firms results in an 8.6% increased likelihood of acquisition from the mean probability. This correlation may exist because public companies, which have been active acquirers of startups, have incentives to acquire startups with similar business models both to reduce competitive threats and to create operational synergies.

Second, patent portfolio size strongly predicts both acquisition and IPO outcomes. The literature documents that companies with substantial intellectual property holdings are associated with higher startup valuations and more likely to secure subsequent funding rounds (Cotei and Farhat (2018), Gaule (2018), Hochberg, Serrano, and Ziedonis (2018), Farre-Mensa, Hegde, and Ljungqvist (2020)). The additional funding might increase the likelihood of successful exits. In my analysis, a one standard deviation increase in the number of patents is associated with a 32.5% increase in acquisition likelihood and a 39.1% increase in IPO likelihood, both measured from the mean probability.

Finally, investment stage is significantly related to exit probability. Investments in early-stage startups reduce exit likelihood by 27.5 percent from the mean probability of exits. This finding is consistent with the literature documenting that late-stage investments are associated with accelerated timelines for successful exits, while generally commanding lower return multiples (Sorensen (2004), Cochrane (2005), Chaplinsky and Gupta-Mukherjee (2016)).

Importantly, these exit predictors are observable to venture capitalists at the time of investment decision-making. These accessible metrics can be utilized by VCs seeking to increase the probability of successful liquidity events, thereby increasing demand for startups exhibiting these characteristics, driving higher entry valuations, and consequently compressing subsequent investment returns. VCs that understand the implications of these predictors will exhibit distinctive investment patterns if they deliberately seek to calibrate risk levels across their portfolios.

Using these metrics, I examine systematic differences in investment choices between venture capital funds with public pension fund LPs and those without such LPs. Employing an indicator variable to denote public pension fund presence in a VC fund's investor base, I find that VC funds with public pension fund LPs demonstrate a significantly higher propensity to invest in startups exhibiting characteristics associated with more predictable exits: greater technological similarity to public companies, larger patent portfolios, and later developmental stages. These findings remain robust when controlling for fund location, sector focus, investment stage orientation, and fund vintage. I also find that these VC funds with public pension fund LPs achieve significantly higher exit rates. They are 54.8% more likely to achieve exits compared to the mean probability of exits, controlling for the interaction of VC fund vintage, stage focus, sector focus, and state fixed effects.

Two distinct mechanisms could explain this observed pattern. First, GPs may deliberately select portfolio companies exhibiting higher probability of exits to ensure more predictable liquidation events when managing capital from public pension funds. Second, public pension funds may strategically allocate capital to venture capital funds that are likely to invest with these specific risk-mitigating characteristics.

To differentiate between these explanations, I first investigate whether the same GP alters investment patterns when managing capital from public pension funds. Specifically, I compare funds with identical stage focus within individual GPs (employing GP-Fund stage fixed effects). This approach assumes public pension funds assess the risk profile of a venture capital fund based on both the specific GP and the fund's declared stage focus. This is a reasonable assumption, as investors' primary evaluation standard is GP performance, which tends to be highly persistent (Kaplan and Schoar (2005), Korteweg and Sorensen (2017)), and the stage focus of VC funds represents their most visible risk characteristic. Consequently, public pension funds likely regard funds with identical stage focus managed by the same GP as broadly similar, implying that the likelihood of receiving public pension fund capital is the same for these funds. Therefore, if GP behavior is influenced by public pension fund presence, only those funds with public pension fund investment should exhibit lower risk profiles.

My analysis reveals that funds with public pension fund LPs systematically target investment characteristics that positively predict exit outcomes, compared with funds with the same stage focus managed by the same GP but without such LPs. Notably, the coefficients remain very close

to those observed in models without GP-fund stage fixed effects, with slightly stronger relationships to lower-risk investments. I further validate these findings by comparing funds with identical stage and sector focus within the same GP, yielding consistent inferences.

With the inclusion of GP-Fund investment focus fixed effects, I subsequently find that funds receiving public pension fund capital exhibit significantly higher portfolio company exit rates relative to other funds with identical investment focus managed by the same GP. The magnitude of this differential effect remains similar to that observed in specifications without such fixed effects, suggesting that the patterns of investing in less risky startups may be driven by GPs' deliberate investment choices.

To address potential selection effects, I investigate whether public pension funds actively choose less risky VC funds. I focus on fund stage focus—the most salient risk characteristic communicated to potential LPs during fundraising. To conduct this analysis, I create a set of public pension fund-available VC fund pairs based on vintage year (to align with public pension fund investment periods) and geographic proximity (to account for location preferences in investment decisions). Specifically, I construct the opportunity set for a public pension fund by identifying VC funds with vintages matching those actually invested in by the public pension fund, while restricting potential funds to those located within the five states geographically closest to the public pension fund's home state. This geographic constraint is empirically justified, as funds within this proximity are more likely to receive capital from public pension funds than those located farther away (Appendix B).

My analysis reveals that early-stage focused VC funds are less likely to receive capital from public pension funds, though the economic magnitude is modest. These funds experience a 0.3 percentage point lower probability of public pension fund investment, representing a 3.75 percent reduction relative to the mean probability. Notably, GP size and prior investment relationships with public pension funds demonstrate substantially stronger associations with public pension fund participation as LPs. A one standard deviation increase in GP size leads to a 4.7 percentage point increase in the likelihood of public pension fund participation in the VC fund, which is 58 percent greater than the mean probability. When a public pension fund has previously invested with a GP, the probability that they will invest in a new fund managed by that same GP increases by 90 percentage points.

Public pension funds exhibit variation in their financial characteristics, although underfundedness represents a common trend across most institutions. I first find that larger public pension funds, those with more favorable funding ratios, and those with superior three-year historical investment returns demonstrate greater propensity to invest in venture capital. These characteristics are also associated with more extensive venture capital investment portfolios.

In the heterogeneous analysis, I examine whether public pension fund size, funding ratio, or historical three-year investment returns influence either GP investment patterns or public pension funds' selection of venture capital funds. The evidence indicates that GP investment choices remain largely unaffected by the financial characteristics of their public pension fund LPs, suggesting that GPs regard these institutional investors as a relatively homogeneous group. This homogeneity likely stems from the fact that public pension funds with relatively stronger financial metrics selectively engage in venture capital investing. I further find that the financial variables of public pension funds have differential effects on their selection of VC funds, but both the statistical and economic magnitude is modest. Past investment relationships with GPs and GP size remain the primary factors driving their investment decisions.

In summary, the results presented in this paper demonstrate that the presence of public pension investors affects VCs' risk-taking. The finding introduces an additional determinant of VCs' risk management. Previous studies have highlighted that contractual incentives shape managers' approach to risk (Buchner and Wagner (2017)), GPs' capital commitments (Jia and Wang (2017)), market cycles (Nanda and Rhodes-Kropf (2013)), and factors such as the experience of GPs also influence their risk-related decisions (Giot, Hege, and Schwienbacher (2014)). This paper shows that investor characteristics can influence VCs' risk-taking. This finding challenges the conventional view that fund managers can disregard investor risk preferences as risk diversification is solely the investor's responsibility. In the VC industry, catering to investor risk preferences may matter to investors due to the substantial size of their commitments and the limited ability to diversify within this segment. Importantly, VCs have strong incentives to maintain investor relationships to secure funding for future funds and protect their reputation in the opaque market.

This paper also highlights the ability of venture capitalists to calibrate the risk profiles of their portfolios through strategic deal selection. This capacity likely arises from structural changes in capital markets: Specifically, the contraction in public listings and the extended-duration companies

remain private (Doidge, Karolyi, and Stulz (2017), Doidge et al. (2018), Davydova et al. (2022), Doidge et al. (2025)). The expanded universe of private companies seeking venture funding provides GPs with sufficient flexibility to select firms exhibiting various risk characteristics, enabling the construction of a targeted portfolio based on LP preferences. This breadth also means venture capital can now accommodate a wider range of investors than before, including mutual funds that must carefully manage liquidity due to their redemption requirements (Kwon, Lowry, and Qian (2020), Chernenko, Lerner, and Zeng (2021)).

Finally, this paper adds a new element to the existing finding on public pension funds' under-performance in private equity (Lerner, Schoar, and Wongsunwai (2007)). Due to the defined benefit structure of their member plans, public pension funds operate under distinctive financial objectives. In particular, liquidity management is an important goal as they experience large outflows due to ongoing benefit distributions. This may incentivize VCs receiving public pension fund capital to prioritize investments with more likely exits, even at the cost of lower returns. Therefore, the documented under-performance might represent an inevitable trade-off in pursuit of more frequent liquidation events.

The remainder of the paper is structured as follows. Section 1 explains the data. Section 2 presents the startup metrics positively associated with successful exits. Section 3 investigates the effect of public pension funds on venture capital investments. Section 4 examines the selection decisions of public pension funds. Section 5 conducts heterogeneous analyses. Section 6 concludes.

1 Data

The primary data used in this study are gathered from VentureXpert. I download all venture capital investments (comprising a startup, a funding round, and a VC fund) made by U.S. VC funds with vintages between 2000 and 2023.[3] VC funds are defined in the paper as those categorized by VentureXpert into 'Balanced Stage,' 'Early Stage,' 'Generalist,' 'Later Stage,' and 'Seed Stage.'[4]

[3]There are several ways to define a fund's vintage year. Common options include the year of legal formation, the year of the fund's initial closing, or the year of the fund's initial capital call. In this paper, I use the year of the fund's initial investment, as it aligns with the fund's first operational activity—its first investment. This date also marks the typical starting point for calculating the fund's gross (portfolio-level) internal rate of return (IRR).

[4]VentureXpert provides a deal-level variable indicating whether a deal is a VC deal. Analyzing data from 1980 to 2023, I found that 'Balanced Stage,' 'Early Stage,' 'Later Stage,' and 'Seed Stage' funds allocate approximately 99% of their deals to VC investments. Generalist funds, on the other hand, allocate around 60% of their deals to VC

The database provides information on the stage of each investment. I categorize both seed-stage and early-stage investments as early-stage investments. I enhance the VC investment data by incorporating information from various sources to support my research.

1.1 Startups' IPO and M&A information

The sample of the startups are those invested by U.S. VC funds with vintages between 2000 and 2023. VentureXpert provides information regarding the public status and company status of startups backed by a VC fund listed within it. However, in some cases, it retains outdated data, and the database does not provide comprehensive information on the exit dates.[5] Therefore, I gather more information from other databases that extensively cover M&As and IPOs. Specifically, I use the SDC Global New Issues database and the SDC's Mergers and Acquisitions database. I focus on completed IPOs and completed acquisitions by corporate acquirers, which serve as reference points for determining the startup's exit date. In addition to the information, I augment the data with the IPO date provided by VentureXpert.

To combine VentureXpert data and the two datasets on IPOs and M&A, I employ the tiered, exact name-matching approach explained in the Online Appendix. The tiered, exact name-matching approach involves finding counterparts in different databases based on exact name matches while gradually allowing for variations in names. This method is used to increase the probability of matches while maintaining the quality of the matches.

After the matching process, I identify the earliest event as the exit event for a startup, whether it is an acquisition by a corporate acquirer or an IPO. After the step, I find that 12,230 startups exited through acquisitions, and 2,007 exited through IPOs among the 53,836 startups in the sample.

In addition to the exit events identified in the previous step, I also use additional information provided by VentureXpert. Two fields in VentureXpert describe an investee company's current status: current public status and company status. If a venture is marked as 'Subsidiary' in the public status field, I interpret this as an exit through an acquisition, even if I can't find the venture

investments. Other private equity funds, such as fund-of-funds, mezzanine stage, and opportunistic funds, do not primarily invest in VC deals.

[5]For example, as of April 2023, Burlington Industries is listed as an active private company in VentureXpert and is not classified as a subsidiary. However, the firm was acquired by International Textile Group in 2003.

in either of the M&A and IPO databases. Similarly, if a startup is labeled 'Public' in the public status field and 'Went Public' in the company status field, I conclude that the company exited via an IPO. I make these adjustments because even though VentureXpert might provide stale data for these fields, the database is unlikely to present false negatives for exits since the default status for a venture is likely to be an active, private company. [6]

As a result of the additional step, there are 532 additional startups that have exited through acquisitions, and 406 more startups that have exited through IPOs. Consequently, acquisition-driven exits constitute 23.7 percent of the sample startups, while IPO-driven exits account for 4.5 percent for the sample startups. The relatively lower frequency of IPOs compared to acquisitions may be attributed to the decline in new public listings. New listings were historically fewer during this sample period—the average annual number of new listings from 2009 to 2016 was 179, compared to 683.5 from 1995 to 2000 (Doidge et al. (2018)).

1.2 Patent Information of Startups

This paper employs metrics such as patent count and the relationship between startup technologies and those developed by public companies. I source patent information for both startups and public firms from Google Patent. In this subsection, I outline the method used to identify patent information associated with startups, while the process for identifying patent data pertaining to public companies is detailed in the Online Appendix.

The United States Patent and Trademark Office (USPTO) discloses patent application publications (pre-grant publications) and patents as part of their patent granting process. Typically, pre-grant publications are released 18 months after the filing date if a patent has not yet been granted. I refer to both types of publications as patent publications.

To identify the patent publications of startups, I need two specific dates for each startup: the founding date and the date the startup either successfully exited or discontinued operations. These dates help determine all patent applications filed with the USPTO as part of the startup's patenting activities.

For startups that have successfully exited, I use the exit date defined in the step above. To identify companies that have ceased operations, I rely on the 'public status' and 'company status'

[6] For those additional exits, I assume startups exit three years post the date of the latest investment from a VC fund.

fields in VentureXpert. A startup is considered defunct if the 'public status' field indicates 'Defunct', or if the 'company status' field shows 'Defunct', 'Bankruptcy - Chapter 11', or 'Bankruptcy - Chapter 7'. I assume that companies went bankrupt five years after receiving their last investment from a VC fund.

For startups that have neither exited nor gone defunct, I assume they are still operating as of the end of 2023.

It is common for the same invention to be published multiple times by the patent office, mostly for administrative reasons. To avoid counting the same invention multiple times, I identify a unique invention by its most recent priority number of patent publications.[7] This ensures each invention is counted only once. I then use the earliest application date of the invention to track patent applications of startups.

This process yields 231,555 unique patent publications and 213,651 unique inventions, which are matched to 16,739 startups out of a sample of 53,836 startups.

1.3 Identifying Public Pension Funds as Limited Partners

The sample of public pension funds consists of those associated with public pension plans listed in the Public Plans Database (PPD), developed by the Center for Retirement Research at Boston College (CRR). The PPD is a comprehensive resource, providing plan-level information from 2001 to 2023 for 228 pension plans. Among these, 121 plans are administered at the state level, while 108 are administered locally. This sample represents approximately 95% of public pension membership and assets across the U.S. according to the CRR.

To compile historical records of public pension funds as limited partners, I manually collect data on private equity holdings of them from various sources, including annual reports, investment performance reports, and other information available on the websites of public pension plans or systems. Additionally, I utilize the Preqin Pro Private Equity database to gather the names of private equity funds invested by the U.S. public pension funds associated with the plans in the PPD. I collect information on the venture capital investments from 2001 to 2023, including those that have never invested in venture capital. The sample includes the funds associated with 219

[7]The priority number of a patent application refers to the identification number associated with the earliest filed patent application in a series of related applications.

plans out of the 228 plans.[8]

To link the VC funds in VentureXpert to those associated with the public pension plans, I use regular expression. For example, a fund labeled 'Providence Equity Partners III' might correspond to versions like 'Providence Equity Prtnrs III', 'Providence Equity Ptrs III', 'Providence Eq Partners III', or 'Providence Eq Ptrs III'. For the remaining public pension funds that are unmatched through the process, I manually search for their names in VentureXpert to collect their identifiers whenever available. Upon completing this step, I find that around 6.8% of VC funds count public pension funds among their LPs.

1.4 Other Data Sources

The financial information of public pension plans is collected from the Public Plans Data. Public company name histories are obtained from the Center for Research in Security Prices and the Securities and Exchange Commission website. The distances between major airports in the U.S. are sourced from the Bureau of Transportation Statistics.

2 Startup Features Associated with Exit Outcomes

IPOs and strategic acquisitions represent successful liquidation events for startups, delivering financial returns for investors. If indicators showing high chances of exits exist, VCs will flock to these startups, driving up valuations and reducing investment returns at exits. This creates an inherent trade-off in investing based on variables capturing exit likelihood. However, for VCs with clear strategic motivations, such as preferring safer bets over risky investments with potentially higher returns, these metrics are useful. This study proposes three variables to measure exit potential that VCs likely consider: a startup's business or technologial proximity to public firms, its patent portfolio size, and its development stage.

Technological or business similarity between startups and existing public companies can be a strong predictor of successful exits, particularly through acquisitions. Public companies often

[8]The nine plans whose fund investment information is not fully or partially available on their websites or in Preqin are Birmingham Retirement & Relief System, Jacksonville General Employees' Retirement Plan, City of Miami General Employees and Sanitation Employees Plan, Phoenix Employees' Retirement System, Jersey City Municipal Employees Pension Fund, Knox County Teachers' DB Plan, City of Birmingham Firemen's and, Policemen's Supplemental Pension System, Little Rock City Firemen Relief and Pension Fund, and Fire Retirement System of Kansas City.

acquire startups with similar technologies to neutralize competitive threats (Cunningham, Ederer, and Ma (2021), Kamepalli, Rajan, and Zingales (2020)) or to achieve strategic synergies, market expansion, and operational efficiency (Higgins and Rodriguez (2006), Makri, Hitt, and Lane (2010)).[9] Therefore, a variable that quantifies a startup's similarity to public companies within the same sector can serve as an indicator of acquisition potential.

The patent count of a startup can also serve as a reliable predictor of successful exits. Patents enhance a firm's intellectual property value, signaling stronger fundamentals to potential acquirers and public market investors. Consequently, patent counts are frequently associated with higher startup valuations (Cotei and Farhat (2018), Gaule (2018), Farre-Mensa, Hegde, and Ljungqvist (2020)). Moreover, patent-rich startups typically demonstrate greater success in securing follow-on financing, which often functions as a critical precursor to eventual exits (Hochberg, Serrano, and Ziedonis (2018)). In summary, allocating capital to startups with substantial patent portfolios represents a strategic approach that trades potentially higher exit probabilities for diminished investment returns.

The third metric for successful exits derives from the venture capital literature. While late-stage investments typically generate lower returns, they exhibit a higher probability of successful exits (Cochrane (2005)).

To test whether the three metrics predict exit outcomes as outlined above, I create a sample of startup-year observations using startups invested in by U.S. VC funds with vintages from 2001 to 2023. The observation period for each startup extends from its founding date until its exit or cessation of operations. For startups without documented exit or bankruptcy information, I assume continued operational status. I restrict the sample observation years to the period between 2001 and 2023, inclusive.

I create a variable for technological similarity to existing public firms using patent applications or patents (collectively referred to as "patent publications") of startups. Specifically, I create a variable $Frac_pubtech$, which is the average percentage of citations to public company patents in a startup's recent patent publications (current year plus the past three years). For startups with patent data gaps in certain years, the most recent available values are used. The values are

[9] Hoberg and Phillips (2010) show acquisitions are more likely between companies that employ comparable product market terminology. Following transactions, stock returns increase when the companies involved use similar product market language. This trend is particularly strong in highly competitive product markets.

then back-filled for periods prior to the patent publication. For startups with no patent records, values are derived by averaging data from similar startups, matched by business description and corresponding year. More details on the matching are available in Appendix A.

Log_patents measures the log of the number of patents (plus one) a startup holds in a given year. *Early_stage_comp* is a dummy variable that equals one if a startup's most recent funding round in a given year was seed or early-stage funding and zero otherwise.

The dependent variables measure the likelihood of a startup's exit. $Exit_5yr$ is a binary variable that equals one if a startup experiences an exit (via acquisition or IPO) within five years from the observation year, and zero otherwise. Acq_5yr is a binary variable that equals one if a startup is acquired within five years from the observation year, and zero otherwise. IPO_5yr is a binary variable that equals one if a startup goes public within five years from the observation year, and zero otherwise. I select a five-year timeframe for exits from each observation year to reflect the practical constraints of venture capital investment horizons. This is a conservative choice, as a VC investing in a startup during the fifth year of the fund's vintage would need the company to exit within the subsequent five years to align with the typical 10-12 year lifespan of a VC fund.

With these variables, I examine the linear relationships between the exit potential metrics and the exit probabilities. The analysis is cross-sectional, comparing exit likelihoods based on startup characteristics in any given year. For this reason, I include year fixed effects. To compare startups within narrower segments in a given year, I also examine the relationships with year-sector fixed effects, comparing startups in the same sector in a given year. To account for any effects stemming from startup location, such as regional innovation ecosystems and local funding environments, I further implement year-sector-startup state fixed effects.

Table 2 reports the results. The technological proximity to public companies strongly predicts acquisitions. When not controlling for a startup's sector, this metric negatively correlates with IPO exits. This relationship may stem from sectoral variations, as startups in certain sectors exhibit greater similarity to public firms while simultaneously experiencing lower IPO probabilities. However, once sector effects are considered, the metric also positively predicts IPOs, possibly indicating that these startups' technologies or business model is comparable to those of publicly listed companies. With year-sector-startup state fixed effects, a one-standard-deviation increase in *Pub_tech* is associated with a 7.3% increase in acquisition probability and a 5.4% increase in IPO

probability, both relative to their respective mean values. The same increase shows a 7% increase from the mean exit rate.

The number of patents a startup holds shows a strong positive correlation with exit likelihood, with t-statistics exceeding 18 for both acquisitions and IPOs. Controlling for startups' sector×state×year fixed effects, a one-standard-deviation increase in *Log_patents* increases acquisition likelihood by 2.8 percentage points, representing an 28.4% higher chance compared to the average acquisition rate. Similarly, a one-standard-deviation increase in *Log_patents* raises IPO likelihood by 0.78 percentage points, representing a 39.1% higher chance relative to the average IPO rate. The same increase shows a 3.6 percentage point increase in the overall exit likelihood, which is 30.2% higher than the mean exit rate.

Investing in early-stage startups lowers their five-year exit probability compared to later-stage startups. Controlling for startups' sector×state×year fixed effects, early-stage investments reduce acquisition likelihood by 2.3 percentage points (23% below the mean acquisition rate) and IPO likelihood by 1 percentage point (50% below the mean IPO rate) relative to later-stage investments. Overall, early-stage investments show a 3.3 percentage point lower exit probability than later-stage investments, representing a 27.5% reduction from the mean exit rate.

The findings identify several metrics that VCs can leverage to evaluate startups' near-term exit probabilities. These metrics create an inherent investment trade-off, as startups with higher exit potential typically attract greater venture capital interest, driving up valuations and potentially compressing returns. However, if VCs with public pension fund LPs prioritize lower-risk investments, these metrics should demonstrate significant correlation with the investment patterns exhibited by such VCs.

3 Investment Choices and Outcomes of VC Funds with Public Pension Fund LPs

The GPs of VC funds hold significant discretion and decision-making power when selecting startups for investment. Typically, securing funds from LPs precedes the selection of startups by GPs. Therefore, by the time GPs actively source potential investment opportunities, they already know who their investors are and what these investors want. While LPs cannot directly influence GPs'

investment decisions, GPs can still take into account LPs' preferences. Therefore, investigating startup selection of VCs provides a way to examine whether and how public pension fund presence impacts VCs' investment decisions.

However, public pension funds also evaluate numerous factors before deciding which VC funds to invest in. Consequently, the presence of public pension funds in a VC fund is the result of individual investment decisions made by them. If public pension funds systematically select VC funds that are predisposed to invest in safer startups, this pattern should not be interpreted as GPs adjusting their investment strategy due to public pension fund LP presence.

To formalize the idea, let us denote $Y_{f,t,i}$ as the dependent variable capturing the investment decision or outcome characteristics of VC fund f with vintage year t for investment i, where each investment represents a startup at a specific funding round. The independent variable of interest, $LP(PPF)_f$, is an indicator variable equal to one when fund f includes at least one public pension fund among its limited partners and zero otherwise. $X_{f,t,i}$ represents a vector of control variables, and $\epsilon_{f,t,i}$ is the error term. The specification below examines the relation between public pension fund presence and VC investment characteristics or outcomes:

$$Y_{f,t,i} = \beta_0 + \beta_1 LP(PPF)_f + X_{f,t,i}\gamma + \epsilon_{f,t,i}, \tag{1}$$

However, the error term, ϵ, potentially encompasses unobservable characteristics that influence public pension funds' VC allocation decisions. Prior literature identifies multiple determinants of limited partners' GP selection process, with GP performance history being particularly salient (Kaplan and Schoar (2005), Gompers, Kaplan, and Mukharlyamov (2016), Barber and Yasuda (2017)). Public pension funds, as some of the largest limited partners in the venture capital ecosystem, may possess several advantages that enable them to access and select superior general partners. Additional considerations including fee structures, geographic proximity, and prevailing market conditions may simultaneously affect public pension funds' allocation decisions and subsequent investment choices of VC funds. This endogeneity concern is particularly difficult to handle, as the inherent opacity of the private capital markets significantly constrains the availability of observable variables that could function as adequate controls or valid instruments.

3.1 Comparing Investments of VC Funds With and Without Public Pension Fund LPs

Setting aside endogeneity concerns, I first examine cross-sectional differences in investment patterns between VC funds with and without public pension fund LPs. This analysis compares investment choices and outcomes conditional on public pension fund presence using Equation (1) with appropriate fixed effects to facilitate comparison among peer VC funds.

To properly identify peer groups, I consider VC funds' vintage, sector focus, and stage focus. Specifically, I incorporate fixed effects for the combinations of these dimensions, as VC funds with similar stage and sector focus represent the most appropriate comparison set.[10] In certain specifications, I further refine this approach by including VC funds' state location, implementing fixed effects for the combinations of VC funds' state, vintage, sector focus, and stage focus to narrow the comparison groups to those VC funds in the same state.

Throughout the analysis, I employ standard errors clustered at the intersection of VC fund's state, vintage, sector focus, and stage focus.

For a control variable, I utilize the cumulative investments of a GP as a proxy for both experience and performance, given the limited availability of GP performance metrics. This approach is supported by prior literature demonstrating that more successful venture capitalists attract greater capital inflows for deployment (Sorensen (2004), Kaplan and Schoar (2005), Gompers, Kaplan, and Mukharlyamov (2016), Barber and Yasuda (2017)).

I first compare deal selections by VC funds conditional on the presence of public pension fund LPs. The dependent variables are the three metrics associated with exit probabilities. Specifically, *Frac_pubtech* and *Log_patents* are the previously defined variables, measured at the time of VC investment. *Early_stage* is a binary variable equal to one if the financing round is classified as seed or early stage funding, and zero otherwise.

Table 3 presents the OLS regression results, revealing statistically significant relationships between public pension fund presence and investment characteristics. VC funds with public pension fund LPs show a tendency to invest in startups with technologies related to public firms, large patent

[10]The inclusion of VC funds' stage focus fixed effects alongside an early-stage investment indicator variable (encompassing both seed and early-stage investments in this study) is feasible as VC funds do not invest exclusively in their stated stage. Seed-focused funds invest in early-stage deals 59.6% of the time, early-stage funds 43%, balanced funds 38.8%, generalist funds 18.7%, and later-stage funds 19% in the sample.

portfolios, and companies raising capital in later funding stages. Controlling for VC funds' vintage × stage focus × sector focus fixed effects, the presence of public pension fund LPs is associated with a 6.2 percentage point decrease in the likelihood of investing in early-stage deals, representing a 14.1 % reduction from the mean probability.

I further examine whether VC funds with public pension fund LPs show different exit likelihoods compared to those without such LPs. For this analysis, I create dependent variables related to portfolio startups' exits. $Exit$, Acq, and IPO are binary variables equal to one if a startup experiences an exit via acquisition (Acq), IPO (IPO), or either ($Exit$) within ten years from the venture capital fund's vintage year, and zero otherwise. I select the ten-year framework as it corresponds to the typical life span of venture capital funds. I maintain the same fixed effects and standard error specifications as in the previous analyses.

Table 4 presents the OLS regression results. When controlling for VC funds' stage focus × sector focus × fund state × vintage fixed effects, investments made by funds with public pension fund LPs are 11.5 percentage points more likely to exit than investments made by funds without public pension fund LPs, representing a 54.8% increase relative to the mean probability of exits. Acquisitions are more likely for investments made by funds with public pension fund LPs by 7.4 percentage points, which constitutes a 43.5% increase relative to the mean probability of acquisitions. For IPOs, the corresponding figures are 4.1 percentage points and 102.5%, respectively.

The findings show that VC funds' strategies to select startups exhibiting lower risk profiles when public pension funds are present as LPs produce the anticipated outcomes: an increased overall likelihood of successful exits among portfolio companies.

3.2 Public Pension Fund Influence on VC Investments: A Comparison of Within-GP funds

The observed linear relationships between investment characteristics or outcomes and the presence of public pension fund LPs do not directly reflect the causal effect of public pension funds on GPs' deal selection processes. To isolate this effect, we must account for potential selection bias stemming from public pension funds' choice of VC funds.

A straightforward approach is to control for the performance metrics of a GP's previous venture capital funds, as the GP's track record is investors' primary consideration when selecting a VC fund

to invest in (Gompers and Lerner (1999), Gompers, Kaplan, and Mukharlyamov (2016)). However, this presents an empirical challenge due to the limited availability of comprehensive performance metrics of VC funds. To address this issue, I employ a within-GP comparison strategy, examining funds managed by the same GP but differing in public pension fund LP participation. This approach controls for GP-specific effects, and given the documented persistence in GP performance (Kaplan and Schoar (2005), Korteweg and Sorensen (2017)), eliminating GP fixed effects partly accounts for performance differentials.

While the within-GP approach addresses some endogeneity concerns, there are other elements public pension funds may consider before making investment decisions. To address this limitation, I incorporate crucial information that is accessible to public pension funds prior to their commitment decisions.

Investment thesis represents one of the most transparent and evaluable aspects of a VC fund. Public pension funds typically conduct thorough reviews of a fund's investment focus, such as stage focus and sector focus, before committing capital. In particular, a VC fund's stage focus is closely related to risk-return profiles of the VC fund. Therefore, public pension funds reviewing a new fund might have the reasonable expectation that funds from the same GP that share investment theses will exhibit similar risk and performance characteristics.

I leverage this institutional feature by implementing increasingly granular fixed effects specifications, beginning with GP-fund stage focus (GP $\times$ stage focus) and adding interactions with fund sector focus (GP $\times$ stage focus $\times$ sector focus) as stage focus is more directly related to riskiness of the investment thesis. This approach effectively compares funds with nearly identical risk profiles managed by the same GP, differing primarily in their public pension fund LP participation. By controlling for the primary dimensions along which public pension funds select VC funds, I can more confidently attribute observed differences to the influence of public pension funds rather than to selection effects.

I further refine the empirical strategy by incorporating additional fixed effects structures to address remaining sources of heterogeneity. When implementing GP $\times$ stage focus fixed effects, I supplement the model with fund vintage $\times$ sector focus $\times$ fund state fixed effects to control for time-varying industry-specific conditions within the VC fund's state that may simultaneously affect fund characteristics and public pension funds' allocation decisions, including political pressure for

in-state investments and mandates for impact investing (Hochberg and Rauh (2013), Barber, Morse, and Yasuda (2021)). Similarly, when employing the more granular GP × stage focus × sector focus fixed effects, I include fund vintage × fund state fixed effects. This comprehensive fixed effects approach minimizes potential confounding factors and facilitates more precise comparison of a GP's funds based on the presence of public pension fund limited partners.

I cluster standard errors at the GP-stage focus level, rather than the more granular GP-stage focus-sector focus level since many GP-stage focus-sector focus combinations contain fewer than 20 observations, making clustering at that level potentially unreliable.

Table 5 presents the results. The findings consistently support the hypothesis that VC funds backed by public pension funds are more likely to select startups that are technologically similar to public firms, possess more patents, and are in later stages of development.

In Columns (4) to (6), which incorporate GP-stage focus fixed effects and vintage-sector focus-fund state fixed effects, the coefficients of $LP(PPF)$ show that within the same-stage focus funds managed by the same GP, those funds with public pension fund limited partners show distinctly different investment patterns relative to their counterparts. The presence of public pension fund LPs is associated with an 8.6% increase in *Frac_pubtech* relative to its mean and a 23.1% increase in *Log_patents* relative to its mean. Additionally, public pension fund LP participation corresponds to a 6.2 percentage point reduction in the likelihood of investing in early-stage startups, representing a 14.1% decrease relative to the mean probability of early-stage investment.

Notably, even with GP × Stage × Sector fixed effects along with vintage × fund state fixed effects (Columns (10)-(12)), the effect of public pension fund participation remains both statistically and economically significant. This persistence across multiple specifications with increasingly granular fixed effects provides robust evidence that the observed investment patterns reflect changes in GP behavior.

Comparing the magnitude of the coefficients across specifications, they are of similar size in magnitude to those in Table 3, showing that it is likely the results in Table 3 are largely driven by the influence of the presence of public pension funds on GPs' investment decisions.

With the same regression specifications, I turn to the effects of public pension fund presence on VC investment outcomes. Table 6 reports the results. VC funds with public pension fund LPs are more likely to experience portfolio company exits than funds with the same stage or sector focus

managed by the same GP. With GP-stage focus fixed effects and vintage-sector focus-fund state fixed effects, the presence of public pension fund LPs leads to a 10.6 percentage point higher exit likelihood, which is 50.5% higher than the mean probability of exit. Importantly, the coefficients are highly similar to those in Table 4.

These findings show VCs with public pension fund LPs substantially enhance their portfolio companies' chances of achieving liquidation events. This is a departure from conventional wisdom, which typically assumes that LP types have no influence on VCs' deal selection. The empirical findings may be explained by institutional settings, where large LPs like public pension funds are valuable investors to VCs for their sizable capital commitment volume and potential to be repeat investors. Public pension plans' defined benefit obligations may incentivize VCs to gear towards more frequent realized returns to accommodate their ongoing liquidity requirements for pension disbursements.

4 Public Pension Funds' Choice of VC Funds

Public pension funds typically conduct rigorous due diligence before investing in venture capital funds, likely selecting partners based on their stated risk preferences.[11] The academic literature has extensively investigated why public pensions allocate capital to alternative assets that belong to high-risk asset classes. Several studies find that this allocation reflects a quest for higher yields driven by underfunded obligations or high discount rates for their liabilities (Pennacchi and Rastad (2011), Mohan and Zhang (2014), Ivashina and Lerner (2018), Lu et al. (2019), Andonov, Bauer, and Cremers (2017)). In this context, public pension funds may select venture capital funds prone to risk-taking.

Conversely, cognizant of the inherent risks associated with venture capital investments, public pension funds may have preference for funds that construct lower-risk portfolios within the venture capital domain. While increasing allocations to both public and private equity, public pension funds might choose to modulate risk exposure within venture capital, acknowledging the distinctive risk characteristics that differentiate this asset class from other risky investment categories.

However, if public pension funds have limited ability to differentiate between funds based on risk characteristics or they do not consider risk in venture capital seriously, they may rely on other

[11] Public pension retirement systems typically disclose their state investment objectives on their official websites.

metrics.

In this section, I examine how public pensions select venture capital funds using both risk-related metrics—specifically fund stage focus—and other characteristics that public pension funds may consider in their allocation decisions: GP size and past investment relationships with the GP.

GP size correlates with multiple factors including performance track record, industry network breadth, and strategic flexibility in terms of deal and fund sizes. This variable is measured by the logarithm of cumulative capital deployed across the GP's historical and current venture capital funds, as GPs typically disclose fund size targets to potential LPs during the fundraising process. Additionally, prior investment relationships with GPs is an important factor, as these relationships reflect both the degree of information asymmetry in the venture capital market and the GP's ability to maintain investor relationships, potentially through customized investment approaches. This is captured through a binary indicator variable that equals one if the public pension fund previously served as a LP in any of the general partner's venture capital funds in the past ten years, zero otherwise.

For this analysis, I construct a sample comprising pairs between public pension funds and potentially available VC funds at the time of investment decisions. For each public pension fund, I define available VC funds using two criteria: (1) geographic proximity—funds located within the five closest states to the public pension fund's state, and (2) temporal alignment—funds with a vintage year matching the year when the public pension fund made investments (proxied by the vintage year of VC funds in which the pension fund actually invested).

While using a VC fund's vintage year as a temporal criterion is straightforward, the geographic proximity criterion requires further explanation. In Appendix B, I analyze interstate investment patterns by examining investments from public pension funds in one state to VC funds within its Nth nearest neighboring states, using a dummy variable for each N in separate regressions. The results demonstrate that the model's goodness of fit peaks when considering VC funds located within the five closest states to the pension fund's home state.[12]

The preference of public pension funds for in-state VC investments has been well-documented in the literature (Cumming and Dai (2010), Hochberg and Rauh (2013)). Beyond in-state invest-

[12]The analysis in Appendix B shows that the home-state dummy variable has the largest coefficient at 0.075, suggesting that VC funds within the same state are most likely to receive investments from local pension funds, consistent with the literature (Cumming and Dai (2010), Hochberg and Rauh (2013)).

ment, proximity to public pension funds matters for several reasons. First, the costs of monitoring portfolio managers decrease when these managers are geographically closer to pension investors. This advantage stems from informational benefits and reduced travel expenses (Coval and Moskowitz (2001), Tian (2011), Ellis, Madureira, and Underwood (2020), Sorenson and Stuart (2001)). Since pension funds must disclose costs related to asset management, they have incentives to minimize expenses associated with manager interactions.

Another explanation lies in the uneven geographic distribution of venture capital firms across states. The clustering of VC funds in certain entrepreneurial hubs may lead public pension funds to allocate capital to VC funds operating outside their home state. For instance, the Providence Employee Retirement System of Rhode Island primarily invests in nearby venture capital centers such as Boston, Chicago, and New York, likely reflecting Rhode Island's limited local venture capital investment opportunities.

I include public pension fund fixed effects to control for time-invariant characteristics of individual pension funds and any time-invariant factors that might influence specific pension fund-VC fund pairings. To account for variations in investment opportunity sets driven by state-level economic conditions affecting VC funds in specific sectors, I include VC funds' state $\times$ sector focus $\times$ vintage fixed effects. This approach enables me to compare VC funds operating in the same state, focusing on the same sector, and established in approximately the same year with respect to their likelihood of receiving public pension capital based on their stage focus, GP size, and past relationship with the public pension fund.

Table 7 presents the analysis of factors influencing public pension fund investment decisions in venture capital funds. In Column (1), I find that public pension funds are less likely to invest in early-stage focused funds, suggesting a preference for lower-risk investment profiles. Column (2) reveals that prior investment relationships with a GP strongly predict public pension fund participation. Column (3) demonstrates that GP size is also a significant determinant of investment decisions.

Column (4), which includes all three variables simultaneously, offers the most comprehensive view. The results indicate that public pension funds are 0.3 percentage points less likely to invest in early-stage focused VC funds, representing a 3.75% decrease relative to the mean probability of investment. The most influential factor is prior investment relationships with GPs, which increases

the probability of receiving public pension fund capital by 90.3 percentage points. GP size also significantly impacts investment decisions, with a one standard deviation increase in GP size associated with a 4.7 percentage point increase in the likelihood of public pension fund participation, representing a 58.6% increase relative to the mean probability.

These findings suggest that while public pension funds show some risk aversion through their modest preference for later-stage funds, institutional factors—particularly established relationships and GP scale—exert substantially greater influence on their allocation decisions.

5 Effects of Public Pension Fund Economic Attributes

Investigating public pension funds' economic characteristics and their impact on investment outcomes is essential for a comprehensive understanding of their venture capital investments. Although a deteriorating funded ratio represents a broad trend among state pension systems, significant variation exists in the financial profiles of public pension funds. This heterogeneity raises important questions about whether the economic differences generate differential effects on previously documented investment patterns.

This section incorporates key financial characteristics of public pension funds—specifically asset size, funded ratio, and historical returns—into the analytical framework established in preceding sections. Before examining the differential effects of the economic variables, I first analyze whether these attributes systematically influence the decision to participate in the venture capital market.

5.1 Public Pension Fund Economic Attributes and VC Investments

I utilize plan-level accounting data to construct economic variables at the public pension fund level. Public pension fund assets represent the aggregated assets of all plans participating in a fund. The funded ratio is calculated as the asset-weighted average of individual plans' funded ratios within a fund. Similarly, the three-year investment return is computed as the asset-weighted average of investment returns across all plans associated with a fund.

Summary statistics for these accounting variables are presented in Column (1) of Table 8. I apply a logarithmic transformation to pension fund assets. The mean funded ratio in my sample is 0.752, which exceeds the figures typically published in government reports. For context, according to the Federal Reserve, the state and local government pension funding ratio in the U.S. stood at 61.6%

in 2022. This discrepancy likely reflects the composition of my dataset sourced from the Public Plans Data, which includes predominantly large pension plans that may maintain stronger funding positions.[13] The standard deviation of 20.6% in funded ratios indicates substantial variation across public pension funds. The mean three-year return is 7.1%, with a standard deviation of 14.9%, exhibiting significant performance differentials among public pension funds.

The significant differences in financial characteristics across public pension funds can influence their decision to participate in the venture capital space. Table 8 compares the characteristics of public pension funds with and without venture capital investments in their portfolios. Asset size appears to be the most distinguishing factor between pension funds that allocate capital to venture capital and those that do not, consistent with the literature (Chemla (2004)). Funds with VC investments display substantially larger asset bases, with a mean logarithmic asset value of 16.401 compared to 14.019 for non-VC investors—a statistically significant difference of -2.38 (t-stat: -14.47).

The funded ratio comparison reveals that pension funds engaging in venture capital maintain slightly healthier funding positions (0.765) relative to their non-VC counterparts (0.742). While this difference is more modest (-0.02) than the asset size disparity, it remains statistically significant (t-stat: -3.77). Historical investment performance also appears to correlate with venture capital allocation decisions. Pension funds with VC exposure demonstrate superior three-year investment returns (7.5%) compared to those without such investments (6.6%) with t-statistics being -1.84.

I connect the public pension fund level accounting data to VC fund investments. I aggregate the assets of public pension funds invested in each VC fund and calculate the public pension fund asset-weighted averages of funded ratios and three-year investment returns for each VC fund.

The summary statistics for these metrics are presented in Column (5) of Table 8. The sample in Column (5) comprises 38,421 venture capital investments made by VC funds backed by public pension fund LPs. Notably, both the mean and median funded ratios and past investment returns are substantially higher than those reported in Column (3), indicating that public pension funds with superior funding status and stronger past investment performance tend to allocate capital more heavily to venture capital investments.

[13] According to Public Plans Data, it covers approximately 230 of the largest state and local pensions in the U.S.

5.2 Public Pension Fund LP Characteristics and VC Fund Choices

In this section, I investigate whether the financial characteristics of public pension funds influence GPs' investment decisions. To examine these potential heterogeneous effects, I construct a series of binary variables capturing different dimensions of pension fund financial health.

First, to assess the impact of public pension fund scale, I create two indicators. $LP(PPF_assets \geq md)$ equals one if a venture capital fund has public pension fund limited partners with combined assets at or above the median, and zero otherwise. Conversely, $LP(PPF_assets < md)$ equals one if a venture capital fund has public pension fund limited partners with combined assets below the median, and zero otherwise.

Second, to evaluate the role of funding adequacy, I establish similar binary classifications. $LP(PPF_funded \geq md)$ equals one if a venture capital fund has public pension fund limited partners with an asset-weighted average funding ratio at or above the median, and zero otherwise. Its counterpart, $LP(PPF_funded < md)$, equals one if a venture capital fund has public pension fund limited partners with an asset-weighted average funding ratio below the median, and zero otherwise.

Third, I define measures based on investment returns. $LP(PPF_ret \geq md)$ equals one if a venture capital fund has public pension fund limited partners with an asset-weighted three-year investment return at or above the median, and zero otherwise. Similarly, $LP(PPF_ret < md)$ equals one if a venture capital fund has public pension fund limited partners with an asset-weighted three-year investment return below the median, and zero otherwise.

Table 9 presents regression results analyzing how public pension fund characteristics influence VC investment decisions using two distinct samples. The first sample includes all VC investments, while the second sample is restricted to investments made by VC funds backed by public pension fund LPs.

In the full sample analysis, I include complementary indicator variables representing both above-median and below-median values. This approach establishes investments made by VC funds without public pension fund LPs as the reference group for comparison. For the restricted sample, I focus exclusively on indicator variables representing above-median financial status. This approach allows me to compare investment decisions made by VC funds backed by economically stronger public pension funds against those funded by financially constrained public pension funds.

The dependent variables across all models capture key startup characteristics at the time of investment, including technological closeness to public firms, logarithm of patent count, and an indicator for early-stage development. To examine how GPs alter their investment choices when public pension funds are present, I use GP $\times$ stage focus fixed effects, alongside fund vintage $\times$ sector focus $\times$ stage focus fixed effects.

The regression results using the full sample reveal a consistent pattern: regardless of whether public pension funds' financial status is above or below median thresholds, VC funds backed by these institutions tend to exhibit similar risk-reduction behaviors.

In the subsample analysis restricted to VC funds with public pension fund LPs, neither asset size nor funding ratio appears to differentially affect investment behavior among these funds. However, when considering three-year investment performance, VC funds backed by public pension funds with better returns are less likely to prioritize acquisition-friendly startups. They are more likely to choose startups exploring technologies that diverge from those pursued by public firms. This pattern likely reflects the sound liquidity position of better-performing public pension funds, which diminishes the pressure on affiliated venture capital firms to prioritize frequent liquidity events.

Collectively, the financial situations of public pension funds do not meaningfully influence investment decisions of GPs. Rather, it is simply the presence of public pension fund LPs that drives these changes in investment behavior.

5.3 Public Pension Fund Characteristics and Public Pension Fund Choices

Public pension funds' financial situations may influence their venture capital investment decisions. This section examines whether public pension funds' selection of VC funds varies based on their asset size, funded ratio, and historical investment returns. For this analysis, I utilize the sample of matched pairs between public pension funds and venture capital funds available for investment at the time of allocation decisions. Using this dataset, I perform regression analyses that incorporate interaction terms between the variables examined in Table 7 and the public pension funds' financial characteristics. I individually analyze the differential effects of the three key pension fund attributes.

Unlike the specifications in Table 7, which include public pension fund fixed effects, I omit these fixed effects to examine the heterogeneous effects of financial variables across public pension

funds. In the final regression specification, I reintroduce public pension fund fixed effects to control for time-invariant fund characteristics. When public pension fund fixed effects are included, the model identifies the effect of economic variables using only within-pension fund variations over time.

Table 10 presents the analysis of how public pension funds' financial characteristics influence their venture capital investment decisions. Panel A examines the differential effects of public pension funds' asset size. The results show that past investment relationships with GPs and GP size remain significant determinants of investment decisions regardless of pension fund asset size. Larger public pension funds demonstrate a greater tendency to maintain relationships with the same GPs while simultaneously showing greater propensity to invest in smaller GPs. However, the economic magnitude of these differential effects is modest.

Panel B investigates the impact of public pension funds' three-year historical returns. The findings show that public pension funds with negative returns exhibit a slight preference for early-stage focused funds, suggesting potential risk-seeking behavior following poor performance, consistent with the literature (Mohan and Zhang (2014)). However, the economic significance is limited. Past relationships with GPs and GP size continue to be influential factors, with limited differential effects based on historical investment returns.

Panel C explores the role of funding ratio. Contrary to expectations that underfunded pensions might engage in excessive risk-taking, better-funded public pension funds demonstrate greater likelihood of investing in early-stage funds. These well-funded institutions also show a slightly reduced tendency to reinvest with the same GPs, though this effect has limited economic magnitude. Better-funded pension plans are more likely to invest in large GPs.

While all three financial characteristics of public pension funds demonstrate somewhat statistically significant differential effects, their economic magnitude is substantially smaller than the impact of prior GP-pension fund relationships or GP size on venture capital fund selection. One plausible explanation may be in the initial screening process evident in Table 8. Public pension funds participating in the venture capital market are already larger and financially stronger, which consequently diminishes meaningful differences in the financial characteristics among these participating funds.

6 Conclusion

This paper examines how public pension funds influence the venture capital industry. The venture capital market operates in an opaque environment with relatively few participants compared to public markets, creating unique incentives for general partners to cater to large institutional investors such as public pension funds. Public pension funds' distinctive liability structure necessitates more predictable exits, even at the expense of potentially lower returns.

The evidence demonstrates that venture capital funds backed by public pension funds disproportionately target startups with characteristics associated with higher exit probability, including technological proximity to public firms, larger patent portfolios, and later development stages. Consequently, these funds experience higher portfolio company exit rates.

While public pension funds show a modest preference for later-stage focused funds, general partners' size and prior relationships exert substantially stronger influence on allocation decisions than risk considerations. Public pension funds' economic variables—such as assets, funded ratio or short-term investment returns—do not significantly affect the main results or demonstrate strong differential effects.

These findings reveal that general partners can calibrate their risk orientation and may actively cater to their limited partners using various investment-level metrics. This strategic flexibility may have been enabled by the evolving private market landscape, where public listings have declined while private firms remain private longer and new venture formation continues to expand. This evolution creates opportunities for venture capitalists to attract investors with diverse risk appetites into the market.

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Table 1: Variable Definitions and Summary Statistics

Panel A reports variable definitions. Panel B presents descriptive statistics including the number of observations (N), mean, standard deviation (SD), 1st percentile (P1), 25th percentile (P25), median, 75th percentile (P75), and 99th percentile (P99).

Panel A	
Startup-Year Observations	
$Frac_pubtech$	The average percentage of citations to public company patents in a startup's recent patent applications (current year plus past three years). For startups with patent data gaps in certain years, the most recent available values are used. For startups with no patent records, values are derived by averaging data from similar startups, matched by business description and corresponding time period.
$Log_patents$	Log of the startup's cumulative patent holdings as of the observation year.
$Early_stage_comp$	A dummy variable that equals one if a startup's most recent financing round in a given year was seed or early stage funding, and zero otherwise.
$Exit_5yr$, Acq_5yr, IPO_5yr	Binary variables equal to one if a startup experiences an exit via acquisition (Acq_5yr), IPO (IPO_5yr), or either ($Exit_5yr$) within five years from the observation year, and zero otherwise.
Investments (Startup-VC Fund-Round of Funding)	
$LP(PPF)$	A dummy variable that equals one if a public pension fund is a limited partner (LP) in a venture capital fund, and zero otherwise.
$Frac_pubtech$	The previously defined $Frac_pubtech$ variable, observed for the startup at the time of investment
$Log_patents$	The previously defined $Log_patents$ variable, measured for the startup at the time of investment
$Early_stage$	A dummy variable that equals one if the financing round is classified as either seed or early stage funding, and zero otherwise.
$Exit$, Acq, IPO	Binary variables equal to one if a startup experiences an exit via acquisition (Acq), IPO (IPO), or either ($Exit$) within ten years from the venture capital fund's vintage year, and zero otherwise.
$Log_GP_past_inv$	Log of the cumulative VC investments made by a general partner (GP), to which the focal VC fund belongs, up to the investment year.
$LP(PPF_assets \geq md)$, $LP(PPF_assets < md)$	Binary variables equal to one if a venture capital fund has public pension fund limited partners with their combined assets above/below the median for $LP(PPF_assets \geq md)/LP(PPF_assets < md)$, and zero otherwise.
$LP(PPF_funded \geq md)$, $LP(PPF_funded < md)$	Binary variables equal to one if a venture capital fund has public pension fund limited partners with their asset-weighted average funding ratio above/below the median for $LP(PPF_funded \geq md)/LP(PPF_funded < md)$, and zero otherwise.
$LP(PPF_ret \geq md)$, $LP(PPF_ret < md)$	Binary variables equal to one if a venture capital fund has public pension fund limited partners with their asset-weighted average past three-year investment returns above/below the median for $LP(PPF_ret \geq md)/LP(PPF_ret < md)$, and zero otherwise.

Panel A - Continued	
Public Pension Fund - Available VC Fund Pairs	
$LP(PPF)$	A binary variable that equals one if the venture capital fund is invested by the public pension fund, zero otherwise.
$Early_fund$	A binary variable that equals one if a venture capital fund is classified as a seed stage or early stage fund, and zero otherwise.
$Same_GP$	A binary variable that equals one if the general partner of the VC fund had the public pension fund as an investor in any of their previous funds launched within the past ten years, and zero otherwise.
Log_GP_size	Log of the cumulative capital deployed by past and current venture capital funds managed by the general partner.
Log_PPF_assets	Log of the public pension fund's total assets under management, calculated by aggregating the asset values of all constituent member plans.
$Returns$	The three-year investment performance of the public pension fund, calculated as the asset-weighted average of three-year investment returns across all of its member plans.
$Funding_ratio$	The funding ratio of the public pension fund, calculated as the asset-weighted average of funding ratios across all of its member plans.

Panel B

Startup-Year Observations

	N	Mean	Std	P1	P25	P50	P75	P99
Frac_pubtech	612279	0.13	0.12	0	0.05	0.11	0.19	0.57
Log_patents	613393	0.27	0.71	0	0	0	0	3.30
Early_stage_comp	613393	0.43	0.50	0	0	0	1	1
Exit_5yr	613393	0.12	0.32	0	0	0	0	1
Acq_5yr	613393	0.10	0.30	0	0	0	0	1
IPO_5yr	613393	0.02	0.13	0	0	0	0	1

Investments (Startup-VC Fund-Round of Funding)

	N	Mean	Std	P1	P25	P50	P75	P99
$LP(PPF)$	227536	0.18	0.39	0	0	0	0	1
Frac_pubtech	196492	0.14	0.12	0	0.06	0.11	0.19	0.56
Log_patents	227536	0.36	0.79	0	0	0	0	3.40
Early_stage	227536	0.44	0.50	0	0	0	1	1
Exit	196726	0.21	0.41	0	0	0	0	1
Acq	196726	0.17	0.38	0	0	0	0	1
IPO	196726	0.04	0.20	0	0	0	0	1
Log_GP_past_inv	215153	4.79	2.32	-0.74	3.29	4.86	6.34	10.67
$LP(PPF_assets \geq md)$	224670	0.09	0.28	0	0	0	0	1
$LP(PPF_assets < md)$	224670	0.09	0.28	0	0	0	0	1
$LP(PPF_funded \geq md)$	224670	0.09	0.28	0	0	0	0	1
$LP(PPF_funded < md)$	224670	0.09	0.28	0	0	0	0	1
$LP(PPF_ret \geq md)$	227536	0.10	0.30	0	0	0	0	1
$LP(PPF_ret < md)$	227536	0.07	0.25	0	0	0	0	1

Public Pension Fund - Available VC Fund Pairs

	N	Mean	Std	P1	P25	P50	P75	P99
$LP(PPF)$	123215	0.08	0.27	0	0	0	0	1
Early_fund	123215	0.53	0.50	0	0	1	1	1
Same_GP	123215	0.03	0.16	0	0	0	0	1
Log_GP_size	123215	3.89	2.47	0	1.96	3.71	5.59	9.88
Log_PPF_assets	114136	17.20	1.19	14.51	16.30	17.21	18.01	19.91
Returns	111739	0.09	0.04	-0.04	0.07	0.09	0.11	0.17
Funding_ratio	114107	0.80	0.16	0.45	0.69	0.79	0.90	1.26

Table 2: Feature of Startup Associated with Exit Outcomes

The table presents how startup characteristics predict exit outcomes within five years. The sample includes startup-year observations from companies funded by U.S. VC funds with vintages between 2001 and 2023. The dependent variables are indicators for exits within five years of the observation year: acquisition (Acq_5yr), IPO (IPO_5yr), or either ($Exit_5yr$). Independent variables include observable startup characteristics in a given year: technological proximity to public companies derived from patent citations, patent count, and early-stage development status. Variable definitions and calculations are in Panel A of Table 1. Reported t-statistics in brackets are computed with standard errors clustered at the startup sector-startup state-year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) $Exit_5yr$	(2) Acq_5yr	(3) IPO_5yr	(4) $Exit_5yr$	(5) Acq_5yr	(6) IPO_5yr	(7) $Exit_5yr$	(8) Acq_5yr	(9) IPO_5yr
$Frac_pubtech$	0.097***	0.113***	-0.015***	0.080***	0.072***	0.008***	0.070***	0.061***	0.009***
	[7.94]	[9.43]	[-7.07]	[7.32]	[6.94]	[5.46]	[6.48]	[5.98]	[5.70]
$Log_patents$	0.057***	0.044***	0.014***	0.055***	0.043***	0.011***	0.051***	0.040***	0.011***
	[25.83]	[25.15]	[18.46]	[25.52]	[24.78]	[18.70]	[25.11]	[24.54]	[18.48]
$Early_stage_comp$	-0.024***	-0.015***	-0.009***	-0.030***	-0.020***	-0.010***	-0.033***	-0.023***	-0.010***
	[-11.91]	[-9.45]	[-11.04]	[-14.07]	[-10.84]	[-15.95]	[-15.42]	[-12.13]	[-18.21]
Year FE	Yes	Yes	Yes						
Year×Sector FE				Yes	Yes	Yes			
Year×Sector×State FE							Yes	Yes	Yes
R^2	0.037	0.028	0.011	0.041	0.032	0.021	0.061	0.052	0.044
Observations	612279	612279	612279	612268	612268	612268	609112	609112	609112

Table 3: Deal Selection - Public Pension vs. Other LP-Backed VC Funds

This table compares deal selection between VC funds with and without public pension fund limited partners. The sample consists of investments made by U.S. VC funds with vintage years between 2001 and 2023. The dependent variables are investment characteristics: a startup's technological similarity to public companies, a startup's patent count, and stage of the funding round. The key independent variable $LP(PPF)$ indicates whether a public pension fund is among the VC fund's LPs. Variable definitions and calculations are in Panel A of Table 1. Reported t-statistics in brackets are computed with standard errors clustered at the VC fund vintage-fund state-sector focus-stage focus level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) *Frac_pubtech*	(2) *Log_patents*	(3) *Early_stage*	(4) *Frac_pubtech*	(5) *Log_patents*	(6) *Early_stage*
$LP(PPF)$	0.012***	0.078***	-0.062***	0.010***	0.071***	-0.059***
	[3.99]	[3.68]	[-4.43]	[2.69]	[2.60]	[-3.39]
Log_GP_past_inv	-0.003***	0.013***	-0.010***	-0.004***	0.014***	-0.016***
	[-6.34]	[3.94]	[-4.11]	[-7.54]	[3.34]	[-5.12]
Vintage×Stage×Sector FE	Yes	Yes	Yes			
Vintage×Stage×Sector×State FE				Yes	Yes	Yes
Adjusted R^2	0.123	0.084	0.133	0.148	0.117	0.173
Observations	185664	215064	215064	185113	214556	214556

Table 4: Investment Outcomes - Public Pension vs. Other LP-Backed VC Funds

This table compares investment outcomes between VC funds with and without public pension fund limited partners. The sample consists of investments made by U.S. VC funds with vintage years between 2001 and 2023. The dependent variables are indicators for exits within ten years of the VC fund's vintage: acquisition (Acq), IPO (IPO), or either type ($Exit$). The key independent variable $LP(PPF)$ indicates whether a public pension fund is among the VC fund's limited partners. Detailed variable definitions and calculations are provided in Panel A of Table 1. Reported t-statistics in brackets are computed with standard errors clustered by VC fund's state × sector focus × stage focus × vintage. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) *Exit*	(2) *Acq*	(3) *IPO*	(4) *Exit*	(5) *Acq*	(6) *IPO*
$LP(PPF)$	0.107***	0.068***	0.039***	0.115***	0.074***	0.041***
	[9.65]	[9.87]	[6.07]	[8.71]	[9.25]	[5.09]
Log_GP_past_inv	-0.017***	-0.019***	0.002**	-0.025***	-0.024***	-0.001
	[-10.90]	[-16.02]	[2.29]	[-15.25]	[-18.41]	[-1.13]
Vintage×Stage×Sector FE	Yes	Yes	Yes			
Vintage×Stage×Sector×State FE				Yes	Yes	Yes
Adjusted R^2	0.07	0.045	0.09	0.111	0.076	0.13
Observations	185877	185877	185877	185324	185324	185324

Table 5: Effects of Public Pension Fund LPs on VCs' Deal Selection

This table examines how public pension fund LPs affect VCs' deal selection, controlling for GP and GP investment strategies (stage focus or sector focus) fixed effects. The sample consists of investments made by U.S. VC funds with vintage years between 2001 and 2023. The dependent variables are investment characteristics: a startup's technological similarity to public companies, a startup's patent count, and stage of the funding round. The key independent variable $LP(PPF)$ indicates whether a public pension fund is among the VC fund's limited partners. Detailed variable definitions and calculations are provided in Panel A of Table 1. Reported t-statistics in brackets are computed with standard errors clustered at the GP-VC fund stage focus level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) *Frac_pubtech*	(2) *Log_patents*	(3) *Early_stage*	(4) *Frac_pubtech*	(5) *Log_patents*	(6) *Early_stage*
$LP(PPF)$	0.018***	0.124***	-0.101***	0.012***	0.083***	-0.062***
	[6.17]	[4.49]	[-6.94]	[3.29]	[3.72]	[-6.55]
Log_GP_past_inv	-0.005***	0.004	0.003	-0.004***	0.011	-0.012***
	[-5.45]	[0.68]	[0.62]	[-8.75]	[1.65]	[-3.75]
GP×Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage×Sector×State FE				Yes	Yes	Yes
Adjusted R^2	0.046	0.041	0.085	0.136	0.1	0.151
Observations	185759	215152	215152	185422	214832	214832
	(7) *Frac_pubtech*	(8) *Log_patents*	(9) *Early_stage*	(10) *Frac_pubtech*	(11) *Log_patents*	(12) *Early_stage*
$LP(PPF)$	0.012***	0.086***	-0.063***	0.007**	0.073***	-0.047***
	[5.46]	[3.86]	[-5.14]	[2.47]	[3.50]	[-4.80]
Log_GP_past_inv	-0.003***	0.015**	-0.006**	-0.004***	0.015**	-0.014***
	[-6.54]	[2.26]	[-2.43]	[-8.49]	[2.00]	[-4.96]
GP×Stage×Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage×State FE				Yes	Yes	Yes
Adjusted R^2	0.108	0.075	0.141	0.13	0.093	0.161
Observations	185686	215087	215087	185649	215053	215053

Table 6: Effects of Public Pension Funds on VC Investment Outcomes

This table examines how public pension fund LPs affect VCs' deal outcomes, controlling for GP and GP investment strategies (stage focus or sector focus) fixed effects. The sample consists of investments made by U.S. VC funds with vintage years between 2001 and 2023. The dependent variables are indicators for exits within ten years of the VC fund's vintage: acquisition (*Acq*), IPO (*IPO*), or either type (*Exit*). The key independent variable $LP(PPF)$ indicates whether a public pension fund is among the VC fund's limited partners. Detailed variable definitions and calculations are provided in Panel A of Table 1. Reported *t*-statistics in brackets are computed with standard errors clustered at the GP-VC fund stage focus level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) *Exit*	(2) *Acq*	(3) *IPO*	(4) *Exit*	(5) *Acq*	(6) *IPO*
$LP(PPF)$	0.105***	0.066***	0.040***	0.106***	0.067***	0.040***
	[7.18]	[8.39]	[4.81]	[9.99]	[8.65]	[8.99]
Log_GP_past_inv	-0.019***	-0.022***	0.003	-0.026***	-0.025***	-0.001
	[-7.40]	[-16.36]	[1.57]	[-20.28]	[-26.10]	[-1.12]
GP×Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage×Sector×State FE				Yes	Yes	Yes
Adjusted R^2	0.038	0.029	0.02	0.093	0.063	0.105
Observations	185971	185971	185971	185634	185634	185634
	(7) *Exit*	(8) *Acq*	(9) *IPO*	(10) *Exit*	(11) *Acq*	(12) *IPO*
$LP(PPF)$	0.094***	0.060***	0.035***	0.094***	0.058***	0.037***
	[6.81]	[8.38]	[4.45]	[9.98]	[8.17]	[7.24]
Log_GP_past_inv	-0.020***	-0.022***	0.002	-0.026***	-0.026***	0
	[-7.10]	[-16.02]	[1.40]	[-15.57]	[-24.52]	[0.01]
GP×Stage×Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage×State FE				Yes	Yes	Yes
Adjusted R^2	0.071	0.052	0.055	0.091	0.066	0.074
Observations	185898	185898	185898	185861	185861	185861

Table 7: Public Pension Funds' Choice of VC Funds

The table examines the likelihood of venture capital funds having public pension funds as limited partners using linear probability models. The sample consists of pairs between public pension funds and potentially available VC funds at the time of investment decisions. Available VC funds are defined as those: (1) located within the five closest states to the public pension fund's state, and (2) having a vintage year matching the year when the public pension fund made investments (proxied by the vintage year of VC funds the pension fund actually invested in). The dependent variable $LP(PPF)$ is a binary indicator that equals one if a public pension fund is among the fund's LPs, and zero otherwise. The independent variables include a binary indicator for early-stage focused funds, a dummy variable indicating whether the venture capital fund is managed by a GP with previous investment relationships with the public pension fund, and GP size measured by the cumulative capital deployed across past and current funds managed by the GP. Detailed variable definitions and calculations are provided in Panel A of Table 1. The t-statistics reported in brackets are calculated using standard errors clustered at the public pension fund level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
		LP(PPF)		
Early_fund	-0.022***			-0.003*
	[-7.25]			[-1.87]
Same_GP		0.975***		0.903***
		[1346.48]		[258.24]
Log_GP_size			0.037***	0.019***
			[64.48]	[23.64]
Vintage×Sector×State FE	Yes	Yes	Yes	Yes
Public Pension Fund FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.143	0.447	0.225	0.467
Observations	123089	123089	123089	123089

Table 8: Summary Statistics of Public Pension Funds and Their VC Investments

The table presents summary statistics for public pension funds' assets, funding ratios, and historical returns. Column (1) includes all public pension fund-year observations from 2001 to 2023. Column (2) presents data for pension fund-years without venture capital (VC) investments in their portfolios, while Column (3) shows data for pension fund-years with VC investments. Column (4) provides statistical comparisons between pension funds with and without VC investments. Column (5) focuses on VC investments (defined as VC fund-startup-funding round combinations) where the VC fund received capital from public pension funds.

	Sample	(1)	(2)	(3)	(4)	(5)
		Public Pension Fund-Year Observations				Investments
		All	VC = 0	VC = 1	diff(0)-(1)	
Log Assets	N	4,466	2,412	2,054		38,421
	Mean	15.114	14.019	16.401	-2.38	20.296
	Median	15.296	14.164	16.423		20.298
	Std	2.184	2.089	1.476		1.633
	t-stat				-44.47	
Funded Ratio	N	4,429	2,378	2,051		38,421
	Mean	0.752	0.742	0.765	-0.02	0.921
	Median	0.766	0.766	0.767		0.892
	Std	0.206	0.220	0.187		0.161
	t-stat				-3.77	
3-Year Investment Returns	N	3,897	1,887	2,010		37,417
	Mean	0.071	0.066	0.075	-0.01	0.083
	Median	0.077	0.073	0.079		0.096
	Std	0.149	0.052	0.201		0.096
	t-stat				-1.84	

Table 9: Public Pension Fund Characteristics and VC Investment Decisions

The table examines the relationship between public pension fund limited partners' characteristics and VC funds' investment decisions. The dependent variables are investment characteristics: a startup's technological similarity to public companies, a startup's patent count, and stage of the funding round. Odd-numbered columns analyze all VC investments made by VC funds with vintages between 2001 and 2023. Even-numbered columns focus on VC investments where the funds received capital from public pension funds. The key independent variables measure public pension fund LP characteristics, such as whether the VC fund has public pension fund LPs whose weighted average funding ratio exceeds the sample median. Detailed variable definitions and calculations are provided in Panel A of Table 1. The t-statistics reported in brackets are calculated using standard errors clustered at the GP-fund stage focus level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Frac_pubtech		*Log_patents*		*Early_stage*	
$LP(PPF_assets \geq md)$	0.012**	0.009	0.104***	0.006	-0.073***	0.016
	[2.58]	[1.56]	[3.59]	[0.15]	[-4.85]	[1.19]
$LP(PPF_assets < md)$	0.011**		0.051**		-0.051***	
	[2.62]		[2.52]		[-4.96]	
Log_GP_past_inv	-0.004***	-0.006***	0.01	0.085***	-0.011***	-0.043***
	[-8.71]	[-5.50]	[1.49]	[2.93]	[-3.48]	[-4.83]
GP×Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage×Sector×State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.132	0.148	0.101	0.098	0.149	0.155
Observations	182858	34447	212002	38063	212002	38063
	(7)	(8)	(9)	(10)	(11)	(12)
	Frac_pubtech		*Log_patents*		*Early_stage*	
$LP(PPF_funded \geq md)$	0.012**	-0.005	0.103***	-0.012	-0.065***	-0.002
	[2.23]	[-1.16]	[3.39]	[-0.30]	[-4.77]	[-0.15]
$LP(PPF_funded < md)$	0.011***		0.054**		-0.060***	
	[3.49]		[2.55]		[-4.56]	
Log_GP_past_inv	-0.004***	-0.005***	0.01	0.085***	-0.012***	-0.043***
	[-8.68]	[-4.63]	[1.55]	[3.09]	[-3.54]	[-4.74]
GP×Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage×Sector×State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.132	0.148	0.101	0.098	0.149	0.155
Observations	182858	34447	212002	38063	212002	38063
	(13)	(14)	(15)	(16)	(17)	(18)
	Frac_pubtech		*Log_patents*		*Early_stage*	
$LP(PPF_ret \geq md)$	0.011***	-0.025***	0.083**	-0.055	-0.069***	0.027
	[2.87]	[-4.21]	[2.19]	[-0.61]	[-5.39]	[0.83]
$LP(PPF_ret < md)$	0.012**		0.070**		-0.054***	
	[2.46]		[2.42]		[-3.28]	
Log_GP_past_inv	-0.004***	-0.006***	0.01	0.085***	-0.012***	-0.043***
	[-8.67]	[-4.89]	[1.53]	[3.08]	[-3.55]	[-4.78]
GP×Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage×Sector×State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.132	0.149	0.101	0.098	0.149	0.155
Observations	182858	34447	212002	38063	212002	38063

Table 10: The Role of Public Pension Fund Characteristics in VC Fund Selection Decisions

The table examines how public pension funds' economic characteristics influence their VC fund selection decisions. The sample consists of pairs between public pension funds and potentially available VC funds at the time of investment decisions. Available VC funds are defined as those: (1) located within the five closest states to the public pension fund's state, and (2) having a vintage year matching the year when the public pension fund made investments (proxied by the vintage year of VC funds the pension fund actually invested in). The dependent variable $LP(PPF)$ is a binary indicator that equals one if a public pension fund is among the fund's LPs, and zero otherwise. The independent variables include a binary indicator for early-stage focused funds, a dummy variable indicating whether the venture capital fund is managed by a GP with previous investment relationships with the public pension fund, and GP size measured by the cumulative capital deployed across past and current funds managed by the general partner. These variables are interacted with public pension funds' economic characteristics. Panel A examines pension fund size, Panel B considers three-year historical returns, and Panel C focuses on funding ratios. Detailed variable definitions and calculations are provided in Panel A of Table 1. The t-statistics reported in brackets are calculated using standard errors clustered at the public pension fund level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A

	(1)	(2)	(3)	(4)	(5)
			$LP(PPF)$		
$Early_fund$	-0.02			0	0.001
	[-0.63]			[0.00]	[0.06]
$Early_fund * Log_PPF_assets$	0			0	-0.001
	[-0.22]			[-0.37]	[-0.42]
$Same_GP$		0.964***		0.777***	0.774***
		[89.91]		[15.78]	[15.26]
$Same_GP * Log_PPF_assets$		0.001		0.008***	0.008***
		[1.03]		[2.84]	[2.84]
Log_GP_size			0.059***	0.049***	0.050***
			[7.06]	[4.24]	[4.15]
$Log_GP_size * Log_PPF_assets$			-0.001***	-0.002***	-0.002***
			[-2.85]	[-2.94]	[-2.92]
Log_PPF_assets	0	0	0.005***	0.007***	0.010***
	[0.23]	[-1.05]	[2.87]	[2.94]	[3.27]
Vintage×Sector×State FE	Yes	Yes	Yes	Yes	Yes
Public Pension Fund FE					Yes
Adjusted R^2	0.148	0.48	0.227	0.496	0.496
Observations	114013	114013	114013	114013	114013

Panel B					
	(1)	(2)	(3)	(4)	(5)
			$LP(PPF)$		
$Early_fund$	-0.031***			0	0
	[-7.09]			[-0.13]	[-0.13]
$Early_fund * Returns$	0.044			-0.076***	-0.076***
	[1.09]			[-2.72]	[-2.71]
$Same_GP$		0.970***		0.922***	0.922***
		[644.84]		[204.91]	[204.49]
$Same_GP * Returns$		0.058***		-0.099**	-0.099**
		[3.33]		[-2.30]	[-2.30]
Log_GP_size			0.038***	0.014***	0.014***
			[32.79]	[12.03]	[11.97]
$Log_GP_size * Returns$			-0.032***	0.018	0.018
			[-2.89]	[1.47]	[1.47]
$Returns$	-0.023	-0.002***	0.117***	-0.023	-0.025
	[-1.09]	[-3.91]	[2.98]	[-0.46]	[-0.48]
Vintage×Sector×State FE	Yes	Yes	Yes	Yes	Yes
Public Pension Fund FE					Yes
Adjusted R^2	0.147	0.487	0.226	0.502	0.502
Observations	111596	111596	111596	111596	111596
Panel C					
	(1)	(2)	(3)	(4)	(5)
			$LP(PPF)$		
$Early_fund$	-0.071***			-0.029***	-0.030***
	[-5.23]			[-3.46]	[-3.51]
$Early_fund * Funding_ratio$	0.056***			0.027**	0.028**
	[3.27]			[2.49]	[2.55]
$Same_GP$		0.975***		0.979***	0.980***
		[195.52]		[51.18]	[50.81]
$Same_GP * Funding_ratio$		0		-0.085***	-0.085***
		[0.05]		[-3.74]	[-3.74]
Log_GP_size			0.029***	-0.003	-0.004
			[9.49]	[-0.82]	[-0.99]
$Log_GP_size * Funding_ratio$			0.009**	0.025***	0.026***
			[2.36]	[4.92]	[4.94]
$Funding_ratio$	-0.029***	0	-0.034**	-0.106***	-0.118***
	[-3.15]	[-0.05]	[-2.36]	[-5.34]	[-5.28]
Vintage×Sector×State FE	Yes	Yes	Yes	Yes	Yes
Public Pension Fund FE					Yes
Adjusted R^2	0.148	0.48	0.227	0.497	0.497
Observations	113984	113984	113984	113984	113984

Appendix A: Methodology for Startup Matching Using Business Descriptions

In this section, I outline the process for finding comparable startups for those lacking patent information. This approach is necessary because the paper employs a metric designed to capture technological relationships between startups and public firms, which relies on patent data. However, only about one-third of these startups have patent application data available (see **Table A.1**). To address this limitation, I infer the values of the metric for startups without patent data by referencing those with available patent data. I use a data source that is available for both types of startups - their business descriptions. The process involves two main steps: first, I extract keywords from each startup's business description using a large language model; second, I use these keywords to identify suitable matches for startups lacking patents.

A.1. Extracting Keywords from Business Description

VentureXpert provides a business description for a startup, typically one or two sentences, averaging around 200 characters. While valuable, this information alone is insufficient for identifying keywords that could improve the chances of finding matches. Therefore, I use a large language model to generate an appropriate number of keywords related to the business description.

To avoid directly inputting the original business description text into ChatGPT, I first replace the startup's name with "the company". I achieve this by using both the startup name listed in VentureXpert and Named Entity Recognition (NER) by SpaCy to identify and remove company names. Whenever a name in the business description matches the one provided in VentureXpert, I replace it with "the company". Similarly, if the NER identifies an organization name, I also replace it with "the company".

Next, I extract nouns from the business descriptions using SpaCy's Named Entity Recognition (NER) to generate an initial set of keywords. However, this set is quite crude, including words that may not necessarily represent the core business keywords of a startup. Nevertheless, when aggregated, these keywords become more informative. I then use this information to refine and generate more relevant business keywords using a large language model.

Specifically, I input the keywords of a startup into the OpenAI ChatGPT 3.5 Turbo model to get the list of business-related keywords. In this step, I prompt the model to suggest items related to the initial keywords, focusing on products, services, and technologies. While a company may have multiple business keywords, I limit the maximum number to forty due to the costs associated with obtaining responses using the large language model.[14] At the end of the process, I obtain a set of forty keywords for each startup in the sample.

[14]The query is "what are some closely related technologies/products/services/businesses for the following keywords? (enumerate about 40 items without explanation): {**keywords**}." The bold word **keywords** is replaced with the list of a startup's keywords.

A.2. Identifying Matches Through Keyword Overlap

Out of a sample of 53,836 startups, 16,739 have patent publications. For each of the remaining startups, I calculate the number of overlapping keywords with each startup that has patent data. This information is stored to apply a threshold, balancing precision and the quantity of matches. I set a minimum threshold of 10 shared keywords for a pair of startups to be considered comparable. By setting the high threshold, I aim to reduce false positives (startups incorrectly identified as similar), thereby improving precision.

A.3. Imputing Technology Characteristics for Non-Patenting Startups

For startups without patent applications, I impute technology characteristics using the mean values from patent-holding startups matched on the keywords and corresponding year.

Table A: Share of Startups with Patent Applications and Those Citing Public Firms' Patents

The table shows the number of total startups, number of startups with patent applications, share of startups with patent applications, number of startups that cite public firms' patents, and share of startups that cite public firms' patents. The sample contains startups backed by US VC funds from 1980 to 2022.

	Total	Technology	Healthcare	Industrials	Consumer Cyclicals
Total number of firms (A)	72471	38400	11139	7569	6057
Number of startups with patent applications (B)	23213	11728	5912	2494	1206
Share of startups with patent applications (B)/(A)	32.03%	30.54%	53.07%	32.95%	19.91%
Number of startups citing public firms' patents (C)	17910	9173	4719	1866	844
Share of startups citing public firms' patents (C)/(B)	77.16%	78.21%	79.82%	74.82%	69.98%
	Consumer Non-Cyclicals	Financials	Basic Materials	Energy	Other
Total number of firms (A)	3083	2573	1423	851	1376
Number of startups with patent applications (B)	523	255	642	284	169
Share of startups with patent applications (B)/(A)	16.96%	9.91%	45.12%	33.37%	12.28%
Number of startups citing public firms' patents (C)	341	167	487	210	103
Share of startups citing public firms' patents (C)/(B)	65.20%	65.49%	75.86%	73.94%	60.95%

Appendix B: Geographical Proximity and Public Pension Fund Investments

Table B: Geographic Proximity and Public Pension Fund Investment Flows into Venture Capital

This table reports OLS regression results using state-pair data across the U.S., including the District of Columbia. For each directed state pair (representing pension fund state → VC fund state), the dependent variable equals one if a public pension fund from the origin state invested in a VC fund in the destination state during 2001-2020, and zero otherwise. The key independent variable, 'Proximate State N', equals one if the VC fund's state is among the Nth closest states to the pension fund's state (including home state), and zero otherwise. *t*-statistics appear in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

	Dep. Var. $I(Pension\ Investments)$						Dep. Var. $I(Pension\ Investments)$					
Proximate State 1	0.075***					Proximate State 6	0.056***					
	[2.93]						[3.35]					
Proximate State 2		0.071***				Proximate State 7		0.059***				
		[3.14]						[3.69]				
Proximate State 3			0.062***			Proximate State 8			0.049***			
			[2.99]						[3.20]			
Proximate State 4				0.068***		Proximate State 9				0.042***		
				[3.59]						[2.85]		
Proximate State 5					0.070***	Proximate State 10					0.046***	
					[3.94]						[3.21]	
Constant	0.107***	0.106***	0.106***	0.104***	0.102***	Constant	0.103***	0.102***	0.103***	0.103***	0.101***	
	[17.55]	[17.23]	[17.01]	[16.55]	[16.16]		[16.11]	[15.70]	[15.66]	[15.55]	[15.14]	
R^2	0.305%	0.349%	0.318%	0.458%	0.549%	R^2	0.399%	0.483%	0.364%	0.289%	0.365%	
Observations	2809	2809	2809	2809	2809	Observations	2809	2809	2809	2809	2809	

	Dep. Var. $I(Pension\ Investments)$						Dep. Var. $I(Pension\ Investments)$					
Proximate State 11	0.050***					Proximate State 16	0.034***					
	[3.55]						[2.69]					
Proximate State 12		0.045***				Proximate State 17		0.032**				
		[3.32]						[2.55]				
Proximate State 13			0.046***			Proximate State 18			0.023*			
			[3.44]						[1.85]			
Proximate State 14				0.042***		Proximate State 19				0.024**		
				[3.21]						[1.99]		
Proximate State 15					0.037***	Proximate State 20					0.028**	
					[2.90]						[2.29]	
Constant	0.100***	0.100***	0.099***	0.099***	0.100***	Constant	0.100***	0.101***	0.103***	0.102***	0.100***	
	[14.71]	[14.59]	[14.27]	[14.15]	[14.05]		[13.93]	[13.75]	[13.93]	[13.60]	[13.18]	
R^2	0.448%	0.391%	0.420%	0.366%	0.299%	R^2	0.257%	0.231%	0.122%	0.141%	0.186%	
Observations	2809	2809	2809	2809	2809	Observations	2809	2809	2809	2809	2809	

Public Pension Funds and Risk-Taking in Venture Capital

Online Appendix

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I provide an extensive overview of the data process applied in this paper. In Section 1, I detail the method used for merging two databases using company names. Section 2 covers the methodology used to identify patent publications associated with public companies. In Section 3, I provide a list comprising all the airports I employ in my research to calculate the distance between two states.

1. Tiered, Exact Name Matching

There are cases where I combine two distinct databases by name of companies. I explain in this section, the approach I take with an example where I find patent publications of a startup.

For each name of startups in VentureXpert and the first assignees in Google Patents, I create three distinct name variables. The first variable, 'Name 1', is derived by replacing "&amp" with "&" in the original name, ensuring minimal alteration. The second variable, 'Name 2', is generated by removing punctuation marks, parentheses, vertical lines, backslashes, and forward slashes from 'Name 1'. Lastly, 'Name 3' is created by eliminating regional information and legal suffixes from 'Name 2'.

The rationale behind these three variables is to prioritize matching by 'Name 1', which preserves the original name's integrity. If unmatched, I proceed with 'Name 2', which has undergone further modification to enhance the matching potential. Finally, for any remaining unmatched names, I utilize 'Name 3'. This tiered approach aims to maintain matching quality while maximizing the number of matched names.

2. Patent Publications of Public Firms

To identify patent applications and patents filed by public companies, I use two databases with the names of these companies.

1.CRSP Name History

A CRSP file contains PERMCO, company names, and the beginning and end dates of each name's effective period.

2.CIK Name History

This dataset is derived from a combination of SEC bulk data on company name history and Compustat name header files. The Compustat files are used to identify the CIKs of companies required to submit 10-K reports. The SEC bulk data on historical company names does not include the first day a CIK became available or the last day it appeared in the system, although it does show all name changes prior to the current one. To address this limitation, the Compustat files are used to infer the first and last effective dates of a company's name.

The final dataset includes GVKEY, CIK, company names from the SEC file, and the effective start and end dates of those names.

I begin the process with public companies from the CRSP dataset by applying the tiered, exact name matching explained above. In the initial matching process, I used the CRSP Name History dataset and the 'Name1' variable, along with date information (using the 'publication date' from the patent dataset and the start and end dates of name effective date). I identified 2,200,725 patent publications. Moving on to the 'Name2' variable, I found 637 additional patent publications. Lastly, when matching by the 'Name3' variable, I obtained 206,167 more matches. During this process, I tallied the number of 'permco' for each publication-publication date pairing. I retained the publication-publication date-permco entries with only one matching 'permco', ensuring no publication-publication date instances had two 'permco' matches.

Next, for the remaining unmatched patent publications, I utilized another dataset for public company names, 'CIK Name History'. Initially, I matched by 'Name1', incorporating date information from Compustat and 'publication date', which resulted in 784,384 additional matches. With 'Name2', I discovered 46,156 more matches. Finally, using 'Name3', I obtained 87,508 further matched patent publications. In each step, I also ensure that there is a unique CIK for every matched publication.

The process results in 3,325,577 unique patent publications for public companies available in the CRSP and Compustat databases.

3. Major Airports by State

I calculate interstate distances using the Bureau of Transportation Statistics' inter-airport database. For each state, I designate a representative major airport, with San Francisco International Airport (SFO) selected for California given its proximity to Silicon Valley's venture capital hub. The following list includes all airports used in calculating state-to-state distances for this analysis.

- Alabama: Birmingham-Shuttlesworth International (BHM)
- Alaska: Ted Stevens Anchorage International (ANC)
- Arizona: Phoenix Sky Harbor International (PHX)
- Arkansas: Bill and Hillary Clinton Nat Adams Field (LIT)
- California: San Francisco International (SFO)
- Colorado: Denver International (DEN)
- Connecticut: Bradley International (BDL)
- Delaware: New Castle (ILG)
- Florida: Orlando International (MCO)
- Georgia: Hartsfield-Jackson Atlanta International (ATL)
- Hawaii: Daniel K Inouye International (HNL)

- Idaho: Boise Air Terminal (BOI)
- Illinois: Chicago O'Hare International (ORD)
- Iowa: Des Moines International (DSM)
- Kansas: Wichita Dwight D Eisenhower National (ICT)
- Kentucky: Cincinnati/Northern Kentucky International (CVG)
- Louisiana: Louis Armstrong New Orleans International (MSY)
- Maine: Portland International Jetport (PWM)
- Maryland: Baltimore/Washington International Thurgood Marshall (BWI)
- Massachusetts: Logan International (BOS)
- Michigan: Detroit Metro Wayne County (DTW)
- Minnesota: Minneapolis-St Paul International (MSP)
- Mississippi: Jackson Medgar Wiley Evers International (JAN)
- Missouri: St Louis Lambert International (STL)
- Montana: Bozeman Yellowstone International (BZN)
- Nebraska: Eppley Airfield (OMA)
- Nevada: Harry Reid International (LAS)
- New Hampshire: Manchester Boston Regional (MHT)
- New Jersey: Newark Liberty International (EWR)
- New Mexico: Albuquerque International Sunport (ABQ)
- New York: John F. Kennedy International (JFK)
- North Carolina: Charlotte Douglas International (CLT)
- North Dakota: Minot International (MOT)
- Ohio: Cleveland-Hopkins International (CLE)
- Oklahoma: Will Rogers World (OKC)
- Oregon: Portland International (PDX)
- Pennsylvania: Philadelphia International (PHL)
- Rhode Island: Rhode Island Tf Green International (PVD)
- South Carolina: Charleston AFB/International (CHS)
- South Dakota: Joe Foss Field (FSD)
- Tennessee: Nashville International (BNA)
- Texas: Dallas/Fort Worth International (DFW)
- Utah: Salt Lake City International (SLC)
- Vermont: Burlington International (BTV)
- Virginia: Washington Dulles International (IAD)
- Washington: Seattle/Tacoma International (SEA)
- West Virginia: West Virginia International Yeager (CRW)
- Wisconsin: General Mitchell International (MKE)
- Wyoming: Casper/Natrona County International (CPR)