Desperate Capital Breeds Productivity Loss: Evidence from Public Pension Investments in Private Equity

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Abstract

I study investment allocations of U.S. public pensions in private equity, and trace their investments to the ultimate micro assets – the target firms which private equity funds invest in, using a novel micro-data on investments in private equity funds and deals, combined with confidential Census data. I show that the most underfunded public pensions match with the smallest private equity funds, and receive lower total returns relative to the least underfunded pensions. Target firms predominantly financed by the most underfunded public pensions experience a -5.2% annual change in labor productivity, and firms financed by other investors experience a +5.2% annual change. Consistent with matching between public pensions and private equity funds, I find that target firms supported by smallest funds face productivity decreases. I introduce a novel instrument of public unionization rates to establish support for underfunded positions causing selection into smaller funds. The paper discusses reasons for the existence of matching.

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1 Introduction

Public pension funds in the United States are one of the largest institutional investors having \$5.3 tn. assets under management as of 2022. The reported underfunded positions of public pensions, that is, the amount by which assets are unable to cover their present value of liabilities, have become significantly worse over time, especially post the financial crisis. Given that these public pensions provide benefits to 14.9 mn. active workers and 12 mn. retirees, it is of key economic importance to understand their asset allocation decisions.[1]

We have also seen that private capital markets, which includes private equity (PE), venture capital, private debt, and other privately traded assets, have grown tremendously over the last two decades with \$5.6 tn. in North America as of 2021. Private equity is two-thirds of private capital. Post receiving capital from investors, private equity funds provide financing to firms. In turn, the growing importance of private equity for the economy is visible as the number of firms supported by PE increased by 106% from 2006 to 2020 providing 11.7 mn. U.S. jobs (Ernst & Young report), while the publicly listed firms have decreased over time. I find that underfunded U.S. public pensions occupy a unique position among investors in PE funds. As U.S. public pensions use the average assumed rate of return on their assets to discount their liabilities, given their desperate need of high expected returns to cover up the shortfall and low fixed income returns, public pensions allocate capital to private equity (Ivashina and Lerner (2018), Giesecke and Rauh (2022)) subsequently gaining access to private firms.

In this paper, I study the outcomes of public pension investments in private equity based on the degree of underfunded positions of pensions. First, I ask which private equity funds do underfunded pensions allocate their capital to? Second, I uncover the microfoundations by studying the outcomes on the end receivers, that is, the target firms, which receive private equity capital provided by underfunded pensions. Lastly, I revisit the literature on overall effects of private equity at target firms, based on a match sample setting studied in Davis, Haltiwanger, Handley, Jarmin, Lerner and Miranda (2014) over a longer time period in light of new inflow of capital from underfunded pensions to private equity funds.

I show that the most underfunded public pensions allocate capital to smaller and newer private equity funds, and receive lower total returns from private equity than the least underfunded pensions. These smaller private funds invest in firms which do worse in terms of labor productivity than firms financed by funds which are supported by other investors. I show evidence to support that smaller funds have more investment links with the most

[1]Statistics quoted from Boston College Retirement Center Public Pensions Data.

underfunded pensions post the financial crisis. Overall, I find that firms financed by private equity buyouts do not undergo increases in labor productivity relative to a control group of firms. The paper suggests that the influx of smaller funds and new capital can be one of the reasons for pulling down the average effect of private equity buyouts on target firms studied in the literature.

I find evidence that public pension funds gamble for resurrection especially post the financial crisis, visible in the thicker tails of return distributions of the most underfunded pensions. The large sized private equity funds have consistent relationships with the least underfunded pensions, but the smaller private equity funds now get more capital from the underfunded pensions. I use public unionization rates as an instrument for underfunded positions of pensions, and show that the more underfunded public pensions invest in smaller private equity funds and get lower total returns from private equity.

This is the first paper which studies the microfoundations of public pension fund investments in private equity. Sparse data availability on investments in private assets and outcomes at target firms, made research in this area difficult. I compile a novel micro-data on private equity buyouts including detailed investments by institutional investors (e.g., CalPERs) in private equity fund familes (e.g., Blackstone Group) and their corresponding funds (e.g., Blackstone Capital Partners VI), and the targets (e.g., Hilton) financed by the individual funds. This allows me to track the entire chain of capital flow from the capital source via the private equity fund to the ultimate recipient. Next, I merge the private equity transactions with the Census Bureau micro-data to track 9,300 PE targets from 1979 to 2019 over time. The advantage of the Census data is that it allows me to track small and private firms over time, which is difficult to do from commercial datasets. I also build a sample of control firms that are comparable to private equity targets but not bought by private equity, constructed based on a granular match of industry, firm size and age, multi-unit status, and buyout year, following Davis et al. (2014). On the real side, my data set covers 7% of total U.S. non-farm payroll employment and 11% of total revenue in real 2020 dollars. I track labor productivity for 6,700 of these targets.

In the first part of the paper, I show that public pension funds have increased allocation to alternative assets by three-fold from early 2000s to end of 2020. As a proportion of all capital flowing into private equity funds, the most underfunded public pensions which have drastically increased their capital commitments post the financial crisis. I observe this along with a deteriorating funded positions of public pensions, and growth of new private equity fund capital after the great financial crisis.

Motivated by these facts, I document assortative matching between the most underfunded public pensions and the smallest private equity funds. This relationship strengthened in the second half of 2000s with the smallest private equity funds having 7.7% more investment linkages with the most underfunded pensions than in the period 1999-2010. I also find that the most underfunded pensions realize lower total private equity returns relative to the least underfunded pensions, indicating that more underfunded pensions match to lower quality private funds. I observe a large overlap between the small and new private equity funds. It is possible that these funds either do not have the expertise and large teams to manage deals, or do not get access to the best deals.[2]

In the second part of the paper, I investigate the returns to underfunded public pensions by studying the target firms underlying the private equity deals. Private equity funds receive returns from deals based on the performance of target firms they invest in, and pension funds recieve returns from their private equity investments net of management and performance fees charged by the funds. Since most of the private equity targeted firms are private and small U.S. firms, I do not observe returns of these companies. Hence, I use the Census Bureau micro-data observe employment, revenue, and wages at the firm level from the Longitudinal Business Database (LBD) following the literature.

I show that characteristics of private equity investors (Limited Partners or LPs) and private equity fund families (General Partners or GPs) correlate with real outcomes at target firms. Among investors, public pensions represent the largest investor type, accounting for 31.3% of all investors and contributing 67% of the capital to PE funds.[3] On average, 20 investors commit capital to a private equity fund, and 1.4 funds finance a target. In the first step, I identify the dominant investor class for each deal based on the capital commitment amount. I show that targets supported predominantly by U.S. public pensions experience an annual productivity change of -0.6% post buyout, while those supported by investors other than public pensions experience a +5.2% productivity change per year. This suggests the specialness of public pensions.

Next, I split the targets financed predominantly by public pensions into terciles based on

[2]In equilibrium, matching between the most underfunded public pensions and small private equity funds can be explained by a number of reasons. Small private equity funds have to engage in marketing efforts to attract capital, and accept low quality capital by the most underfunded pensions. Another explanation is that more underfunded public pensions are smaller in size, and size based relationships between investors and funds are prevalent (Lerner, Mao, Schoar and Zhang (2022) document preferential access of capital between top investors and top general partners).

[3]This number over represents the involvement of public pensions in private equity funds. However, Brown, Harris, Jenkinson, Kaplan and Robinson (2015) shows comparability across databases which does not refute the importance of public pensions in private equity.

the degree to which they are underfunded at the time of capital commitment. As in the literature, I define the extent to which pension funds are underfunded as one minus the ratio of assets to liabilities. I show that target firms whose dominant source of private capital are the most underfunded public pensions experience a larger decrease in revenue and lower decrease in employment as compared to the other investor category firms. This results in a labor productivity change of -5.2% for firms supported by the most underfunded pensions, as compared to +5.2% for other investors. I weight underfunded positions of pensions by the amount of capital committed. The more private equity capital in a deal is sourced from underfunded pensions, larger the subsequent productivity loss of the target. These cross-sectional differences get larger in the second half of the sample, when more private equity funds got more capital from the most underfunded public pensions.

Since capital flows from investors to firms via funds, and the decision of investments in firms is made by the private equity funds and not the investors, I study the differences in target firms' outcomes based on characteristics of private equity funds. I split target firms based on the size of the fund family financing the deal. I measure size as the sum of book value of capital committed by LPs to GPs, additional market value of investments based on performance, and capital yet to be called by GPs ("dry powder"). Bigger private equity fund families also have larger teams, and management staff. They are also representative of better quality following the mutual fund literature (Berk and van Binsbergen (2015)). When more than one fund family is financing a deal, I weight the quality measure by the number of funds (per family) involved in the deal.

I find that targets financed by the smaller private equity funds experience largest productivity declines. For instance, firms supported by fund families in the bottom 25th size percentile experience a -2.9% annual labor productivity change as compared to firms in the top 75th percentile which face a +1.4% productivity change. The negative productivity changes are larger, farther down the fund family size distribution we are. I only observe total wages at firms as one of the costs incurred by target firms, and find the patterns hold after taking them into account. Similar to the analysis of the investors, the cross-sectional differences get larger in the second half of the sample.

Decreasing labor productivity along the private equity fund family size distribution specially in the second half of the time period is consistent with decreasing returns from private equity over time (Gupta and Van Nieuwerburgh (2021)), suggesting a decreasing returns to scale at the industry level. Capital from underfunded public pensions fuels the growth of more and smaller private equity funds, resulting is more projects being financed in the private markets, pulling down the average returns over time. This phenomenon is different from decreasing returns at the fund level. The cross-sectional differences in labor productivity post private equity deals arises in splits of firms based on both, investor and private equity characteristics, supporting the assortative matching between investors and private equity funds documented in the first part of the paper.

Why do underfunded pensions sort with smaller private equity funds? I show that the distribution of private equity returns received by the most underfunded pensions post the financial crisis have thicker tails relative to the least underfunded pensions. This supports that the underfunded pensions gamble for resurrection in search for higher returns. The relationships of investors with the biggest funds remains consistent over time, while the smaller private equity funds receive more capital from the most underfunded pensions. It is possible that the small and new funds promise higher returns, or underfunded pensions are taking a risk without information. This is difficult to disentangle as I do not see the contractual agreements or expected returns of private equity funds advertised to pensions.

Is it underfunded positions or other characteristics of public pensions correlated with underfunding ratios, responsible for the match between public pensions and private equity funds? One potential confounder is that the most underfunded pensions might be less skilled in selecting investments. In order to cleanly identify the effect of underfunded pensions, I use a novel instrumental variable (IV) for the underfunded positions of pensions: public unionization rates, also referred to as public union density. Higher union density amongst state employees is associated with higher underfunded positions of public pensions.

This instrument is valid under two identifying assumptions. First, union density amongst state employees affects asset allocation by public pensions to private equity funds only through underfunded ratios of pensions (exclusion restriction). This is a plausible assumption as public union density is at the state-year level and not the pension-year level. To address reverse causality concerns, i.e., more underfunding might lead to higher unionization amongst state employees, I take one year lagged values of unionization rates. Second, higher union density should lead to higher underfunded ratios at pensions (relevance condition). Public unions are associated with higher bargaining power and higher wages (Booth and Chatterji (1995)), which increase pension underfunding ratios. To support the argument for underfunded positions and against political motives of local pensions, I limit the support of target firms from out-of-state pensions, and find consistent results.

Using public union density as an instrumental variable for underfunded positions of pensions, I show that more underfunded pensions allocate capital to smaller private equity funds. More unionized pensions earn lower total PE returns. I sort public pension financed firms by their corresponding state union rates. I find that targets whose capital source is the most unionized public pensions experience a -6.7% productivity change relative to the other investor category.

In the last part of the paper, I revisit the existing literature, motivated by Davis et al. (2014), on the effects of private equity buyouts on target firms relative to a control group of firms to connect the marginal and average results. In this part, I consider all private equity deals in my sample matched to the U.S. Census data and evaluate them against a control group of firms based on existing literature (in the same industry, firm age and size category, multi/single unit, and year of buyout, which have not undergone a private equity deal). For the sample period of 1997 to 2018, I find labor productivity declines by 0.4% at target firms relative to control firms. For the average target, this corresponds to a $1,600 drop in revenue per employee post buyout. For firms in the manufacturing sector, I use total factor productivity (TFP) measures using detailed cost and factor input data from the Census of Manufactures (CMF) and the Annual Survey of Manufactures (ASM). I find no significant improvements in productivity, measured either by TFP (-0.5%) or labor productivity (-3.5%). The null result of labor productivity in the full sample masks an important change in the time series. For private deals from 1999 to 2011, I find a +7.3% two year cumulative productivity change post buyout, similar to Davis, Haltiwanger, Handley, Lerner, Lipsius and Miranda (2019) which find a +7.5% two year productivity gain for the same time period. For deals from 2011 to 2018, I find a -5.4% two year productivity change. The insignificant labor productivity effects for the full sample are pulled down by negative effects in the second half of the period. This coincides with a rise in the share of private equity capital sourced from underfunded pensions, more underfunded pensions receiving lower return from private equity, and target firms financed by underfunded pensions facing large negative changes in labor productivity. Influx of capital from public pensions fueling the growth of private equity funds is one of the reasons which can explain the aggregate trends. It is also possible for other changes in the economy to happen at the same time.

My paper has important policy implications for fragility of state and local retirement systems. My paper lends support to the discussion of public pension liability accounting using risk free interest rates (Novy-Marx and Rauh (2009)). Since U.S. public pensions use their assumed rate of return on assets to discount liabilities, they have an incentive to invest higher proportion of assets to PE, but eventually allocate to smaller private equity funds which are investing in worse projects, or do not have the expertise to generate higher returns.

Related Literature. My paper contributes to three main strands of literature. First, I contribute to the research studying pension funds' investment decisions and its incentives

(Andonov, Bauer and Cremers (2017), Andonov, Eichholtz and Kok (2015), Andonov, Hochberg and Rauh (2018), Korteweg, Panageas and Systla (2023), Chemla (2004)). Ivashina and Lerner (2018) and Giesecke and Rauh (2022) document increases in private market investments by public pensions. Peng and Wang (2019) show that pension funds' investments in private assets might be a short term solution. My paper is the first to study the underlying assets of public pension investments in private equity, by connecting the investments in individual private funds to deals made by those funds, which are largely opaque and bilateral. I compile a novel granular dataset to study this.

Second, my paper complements the existing literature on relationships between investors and funds (such as Lerner, Schoar and Wongsunwai (2007) documenting heterogeneity in returns realized by investors, Lerner and Schoar (2002) for investors' liquidity considerations, and Begenau and Siriwardane (2020) studying fees paid). In this paper, I show assortative matching between investors and funds. I propose the supply of capital from underfunded pensions fueling the growth of small private equity funds, as one of the explanations for decreases in productivity at target firms in the average. Moreover, the existing literature either studies effects of private funds on firms or investments by investors into funds. This paper studies the full chain of capital flow in private markets from end investors to end firms.

Third, I contribute to papers which study financial and real effects of private funds. For financial effects: Kaplan and Schoar (2005), Korteweg and Nagel (2022), and Gupta and Van Nieuwerburgh (2021) study fund returns, Kaplan, Klebanov and Sorensen (2008) discusses CEO characteristics, Ivashina and Kovner (2011) documents private equity advantage for favorable loan terms, and Bernstein, Lerner and Mezzanotti (2018) discusses if private equity contributes to financial fragility during the financial crisis. The existing research on the real effects of private equity is sparse and inconclusive. The private industry is opaque, involving many layers of financing, and data is limited. Existing research either relies on survey data or case studies (Jensen (1999), Baker and Wruck (1989), Metrick and Yasuda (2010), McCourt (2017)), or studies specific industries (Bernstein and Sheen (2016), Howell, Jang, Kim and Weisbach (2022), Ewens, Gupta and Howell (2022), Liu (2021)), thus not giving us representative answers. Only two papers directly study the effects of private equity buyouts on employment and productivity in the aggregate (Davis et al. (2014), Davis et al. (2019)). Davis et al. (2014) studies 3,200 buyouts until 2003 when private equity only started booming, finding increases in TFP for manufacturing targets. Davis et al. (2019) considers private equity deals until 2011 and finds heterogeneous effects based on type of the firm targeted, and finding increases in labor productivity overall.

I study a larger and longer sample period, tracking 9,300 targets from 1976 to 2019, spanning across 22 industries covering 7% of total U.S. non-farm payroll employment and 11% of total revenue. While I find positive productivity changes in the first half, I find negative productivity changes post 2011. The existing literature is silent about the investor in the private equity deal. This is the first paper to study how the sources of capital, the investors and private intermediaries, particularly underfunded public pensions play a role in explaining the changes in labor productivity at target firms post the financial crisis via assortative matching with smaller private funds. Broadly, I also contribute to the body of work on capital allocation and reach for yield.

I develop a novel comprehensive database connecting different investor types, including public pensions, private pensions, insurance companies, sovereign wealth funds, and family offices across countries to private equity funds, and ultimately to firms and establishments financed by those funds. Along with the target firms merged to the U.S. Census micro-data, and public pension fundamentals from FOIA requests and Public Pensions Database, this is the first study to exploit such a granular and extensive data of private markets.

Overview. Rest of the paper is structured as follows. Section 2 gives an overview of the data and presents institutional details. Section 3 discusses public pension investments in private equity. Section 4 documents heterogeneity in target firms based on investors and private equity funds. Section 5 presents support for the notion of desperate capital. Section 6 relates cross-sectional estimates to the aggregate. Section 7 discusses economic and policy implications. Section 8 concludes and discusses areas for future research.

2 Data and Institutional Background

2.1 Data

I construct a comprehensive dataset of investments in private equity, combined with deals between private equity funds and target firms, and track target firms over time. The sections below describe these in detail.

2.1.1 Investors, Public Pension Funds, and Private Equity Transactions

The primary dataset is from Preqin. On the supply side of capital, I obtain investments by institutional investors such as public pension funds, private pensions, endowments, family offices, and insurance companies in private equity fund families and their individual funds. I observe cash flows for these investments, including capital commitments, capital calls, distributions, etc. The main advantage of this data over that used in prior work are the connections between investors and individual private equity funds within the private equity fund family, which allows me to study capital flow to firms accurately and at a granular level. On the demand side, I obtain deal-level transactional data between private equity funds and firms. I observe the private equity fund and family financing the deal, target firm, and the deal date. I also obtain a comprehensive list of attributes of private equity funds including their location, vintage, fund family, and industry focus.

I consider private equity funds whose main strategy is "buyout". Due to differences in structure, I do not consider venture funds that invest in startups. I am unable to distinguish the type of deal within a buyout strategy because of sparse data. The data on investors, private equity funds, and firms spans across all countries, both developed and emerging, from 1979 to 2021, with better coverage post 2000. For this paper, I focus on U.S. public pension funds and U.S. target firms.

I merge the supply side and demand side data, to obtain the full chain of capital flow in private markets from end investor to private equity funds, and subsequently to end recipients (firms). There is no one dataset which covers PE transactions comprehensively. I supplement Preqin with news sources and manual web searches to verify deals, identify names of target firms before and after buyout, and ensure accurate addresses.[4]

I complement the private market capital flow data constructed from Preqin with the Public Pension Fund Database (PPD) and 75 Freedom of Information Act (FOIA) responses from individual state pensions[5], which gives financials and investment allocations of U.S. public pensions by asset class over time. I track 210 U.S. public pensions, covering 95% of pension fund assets. I connect data on public pension financials from PPD and FOIA requests with their investment allocations to individual funds from Preqin via a manual match on pension fund name. I obtain the hierarchy of state pension funds from state websites, and merge exact entities if available in both datasets and consider the parent entity, if not available.

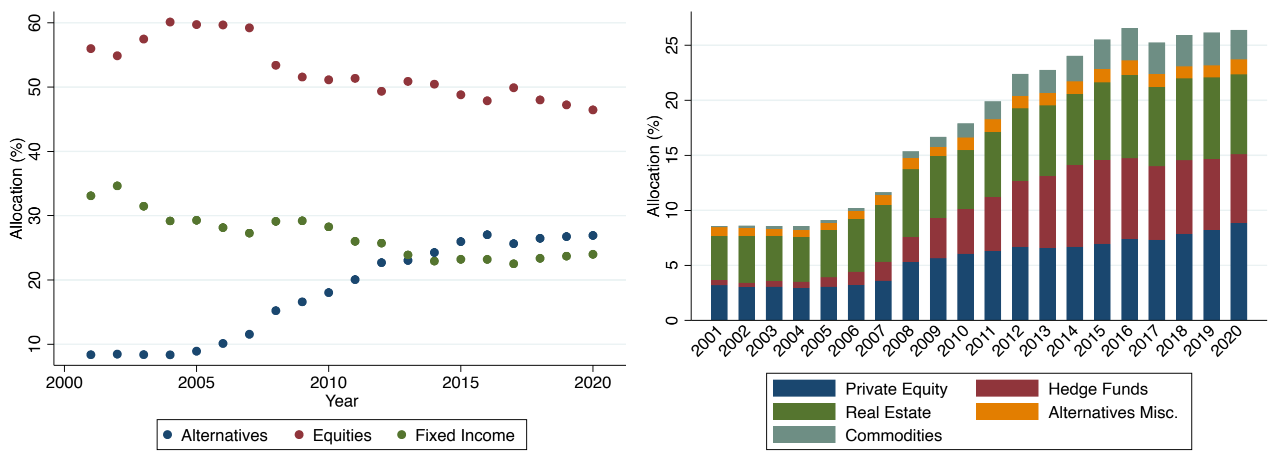
Figure 1 shows asset allocation of U.S. public pensions increased from 8.4% (2001) to 27% (2020), while their allocation to public equities and fixed income decreased over time. Within alternative assets, private equity has occupied a substantial share. Figure 2 shows that within private equity funds, the share of capital committed by the bottom most tercile of underfunded public pensions, defined in the year prior to commitment, increased after the financial crisis. It is expected for investments to take a couple of years to appear, as the first

[4]Preqin obtains most of its data for public pensions through FOIA requests, and its coverage is very comprehensive for public pensions (Begenau, Robles-Garcia, Siriwardane and Wang (2020)).

[5]I am grateful to Korteweg et al. (2023) for sharing their FOIA requested data.

few years of a fund is invested in raising capital from investors. This pattern coincides with increase in underfunded positions of public pensions and new capital entering the private equity fund industry post the financial crisis (Figure 13-14).

Figure 1. Portfolio Allocation of U.S. Public Pensions Over Time



(A) Across asset classes

(B) Within alternative assets

Notes: The y axis represents portfolio allocation of assets as a percentage of total assets. Panel A shows asset allocation of U.S. public pensions *across* asset classes over time. Panel B focuses on *within* the alternative asset class. Data are sourced from Public Plans Data (link: `https://publicplansdata.org/`)

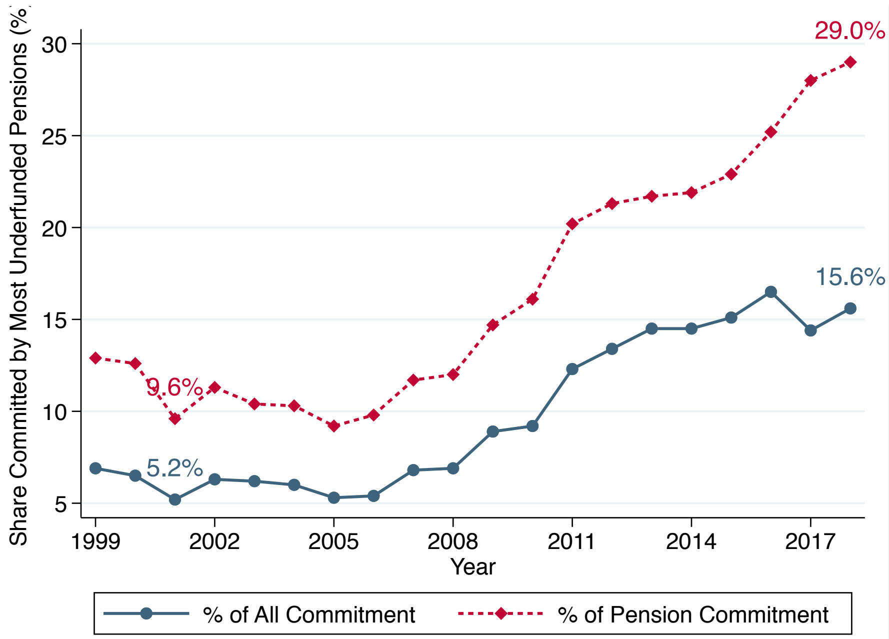
2.1.2 Matching with Census micro-data

To track the underlying firms of public pensions' investments in private equity over time, I merge the public pension investment and private equity data with the Census Bureau micro-data. As most of the firms are private, Census data provides the most comprehensive information for my sample. First, I merge the target firms with the Standard Statistical Establishment Listing (SSEL) database. SSEL provides names and addresses of all establishments in the U.S., with establishment and firm identifiers connecting entities over time.[6] I use name and address fields in the SSEL and the buyout firms to merge these two datasets. Since targets might undergo name and entity changes post buyout, I use names and addresses one year pre-buyout in SSEL.[7] Post merging the buyout deals with SSEL, I use firm-establishment linkages to combine all establishments at the firm level across years for the matched targets.

[6]SSEL updates names and addresses every year from 1976 to 2019. An establishment is the unit of observation in SSEL.

[7]Merge is robust based firm characteristics one to two years pre-buyout.

Figure 2. Capital Commitment by the Most Underfunded Public Pensions Over Time



Notes: The figure plots three year moving averages of shares committed by the most underfunded public pension tercile. The figure uses all PE buyouts. Results are similar when using private equity transactions matched to Census micro-data. Data are sourced from Preqin, Public Pensions Database, and FOIA requests.

Second, I link the merged private equity investments, transactions, and SSEL data to the Longitudinal Business Database Revenue Enhanced (LBDREV).[8] An establishment is the lowest level of aggregation in the LBD. The LBD covers all business establishments in the U.S. private non-farm sector with at least one paid employee (Jarmin and Miranda (2002)), covering approximately 7 million firms and 9 million establishments as of 2019. Connecting the target firms with the LBD allows me to observe granular changes in employment and revenue at firms over time. I obtain employment, pay, revenue, industry affiliation, along with time consistent linkages between firms and establishments. Target firms matched to the LBD account for 7% of total non-farm business employment and 11% of revenue in 2018. This corresponds to 10.9 mn. jobs and $3.1 tn. revenue (Figure 15).

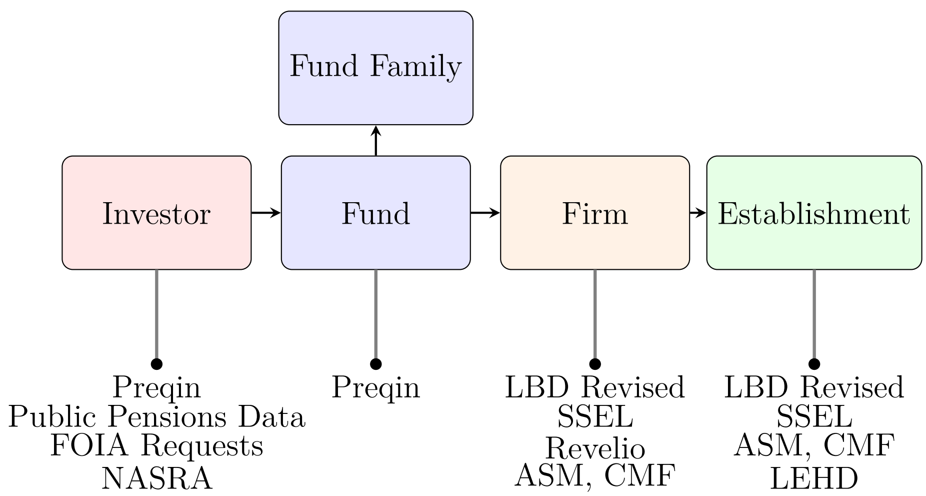
There are multiple hurdles in studying target firms post private equity buyouts. First, private equity funds have a median holding period of six years, and more recently prefer to "flip" their investments even faster (Kaplan and Strömberg (2009)). Second, changes in firm names are not uncommon post buyout, as the target can undergo another merger in later

[8]LBDREV is the revenue enhanced and revised version of the original Longitudinal Business Database (LBD). The major improvement of LBDREV over LBD is consistent longitudinal firm and establishment identifiers across time. I will refer to LBDREV as LBD going forward. I give a full description of the data and matching in detail in Appendix D and E.

years. To encounter these concerns, I study target firms around a 5-year window relative to buyout.

Third, Annual Survey of Manufacturers (ASM) and the Census of Manufacturers (CMF) give detailed cost measures for manufacturing firms in the sample. Manufacturing targets allow me to study an additional and common productivity measure, total factor productivity. Figure 3 shows a visualization of the data structure and its sources.

Figure 3. Visualization of Data and its Sources



Notes: The figure draws connection between the data and its sources. LBD – Longitudinal Business Database. SSEL – Standard Statistical Establishment Listing. ASM – Annual Survey of Manufactures. CMF – Census of Manufactures. LEHD – Longitudinal Employer-Household Dynamics. FOIA – Freedom of Information Act. NASRA – National Association of State Retirement Administrators.

2.1.3 Other Data

I obtain unionization rates at state-year level from the Current Population Survey. Further, I obtain monthly employment at target firms from another private data provider, Revelio Labs. The data is sourced from professional profiles online, job postings, government data such as immigration filings, social security administration data, and voter registration data. I match the Preqin target companies with employment data from Revelio for robustness.

2.1.4 Final Sample

The final sample has 9,300 target firms and 190,000 establishments.[9] Table 1 provides a summary. For 6,700 firms, I am able to construct labor productivity defined as real revenue

[9]This number corresponds to PE targets for which I can construct the control group. More detail in Section 6.1.

per employee. My main sample period is 1997 to 2018. Panel A shows private equity target firms have on average 1,700 employees, $571 mn. revenue in 2020 U.S. dollars, and generate $400,400 revenue per employee.

Table 1. Summary Statistics of Private Equity Targets, 1997-2018

	Count (1)	Mean (2)	Median (3)	Std Dev (4)	25th Pct (5)	75th Pct (6)
Panel A: All Targets						
Employment	9,300	1,500	62	11,000	15	300
Targets with Productivity						
Employment	6,700	1,700	76	11,000	22	350
Revenue (000s)	6,700	571,000	19,000	4,712,000	4,900	88,500
Revenue/Employment (000s)	6,700	400.4	235.7	1,300	139.5	417.3
Panel B: By LP Category						
Most Underfunded Pensions						
Employment	1,200	1,200	69	6,100	20	322
Revenue (000s)	1,200	427,000	17,000	3,015,000	4,800	73,000
Revenue/Employment (000s)	1,200	381.2	238.4	644.8	144.8	402
Medium Underfunded Pensions						
Employment	1,300	1,300	65	7,000	19	292
Revenue (000s)	1,300	499,000	17,500	6,069,000	4,100	77,000
Revenue/Employment (000s)	1,300	389.7	233.5	834.9	138.6	420.8
Least Underfunded Pensions						
Employment	1,400	3,500	171	18,500	30	1,057
Revenue (000s)	1,400	1,108,000	45,500	6,071,000	7,100	267,000
Revenue/Employment (000s)	1,400	454.9	252.5	2,534	142.1	446.7
Other Investors						
Employment	1,300	1,500	75	9,200	21	325
Revenue (000s)	1,300	569,000	19,500	4,902,000	5,100	79,500
Revenue/Employment (000s)	1,300	399.6	239.8	612.3	141.8	427.1
Panel C: By GP Category						
Bottom 25th Percentile						
Employment	700	1,000	74	4,800	26	287
Revenue (000s)	700	385,000	19,000	2,396,000	6,000	63,000
Revenue/Employment (000s)	700	391.0	236.3	616.2	132.9	438.6
Top 75th Percentile						
Employment	4,800	1,900	80	11,500	21	424
Revenue (000s)	4,800	653,000	20,500	5,255,000	4,800	104,000
Revenue/Employment (000s)	4,800	407.6	240.2	1,443	141.8	421.9

Notes: PE deals from 1997 to 2018 are considered. Medians and percentiles are calculated according to Census disclosure rules. Observations are rounded to meet Census disclosure requirements. Panel B splits targets based on dominant investor type, which is defined by the maximum capital committed by the investor. Funded ratios are aggregated at the firm level using commitment amounts as weights. Panel C splits targets based on size of the fund family financing the target, proxied by average market value of assets.

Out of the 6,700 firms, I match investor identities and characteristics for 5,200 and private equity information for 5,500. 850 fund families and their 2,200 funds, supported by 3,300 investors invest capital in leveraged buyouts through commingled funds. On average, 20 investors finance a private equity deal through 1.4 funds.

In Panel B, I split the targets by investor category. I identify the dominant investor for a deal based on the maximum amount of capital committed by each type of investor. The "other investor" category is largely supported by insurance companies, family offices, endowments, funds of funds. Further, I split the public pension supported deals into terciles based on underfunded positions of pensions. The most underfunded pension supported deals have an average revenue per employee of $381,200 while the least underfunded pension supported deals have an average labor productivity of $454,900.

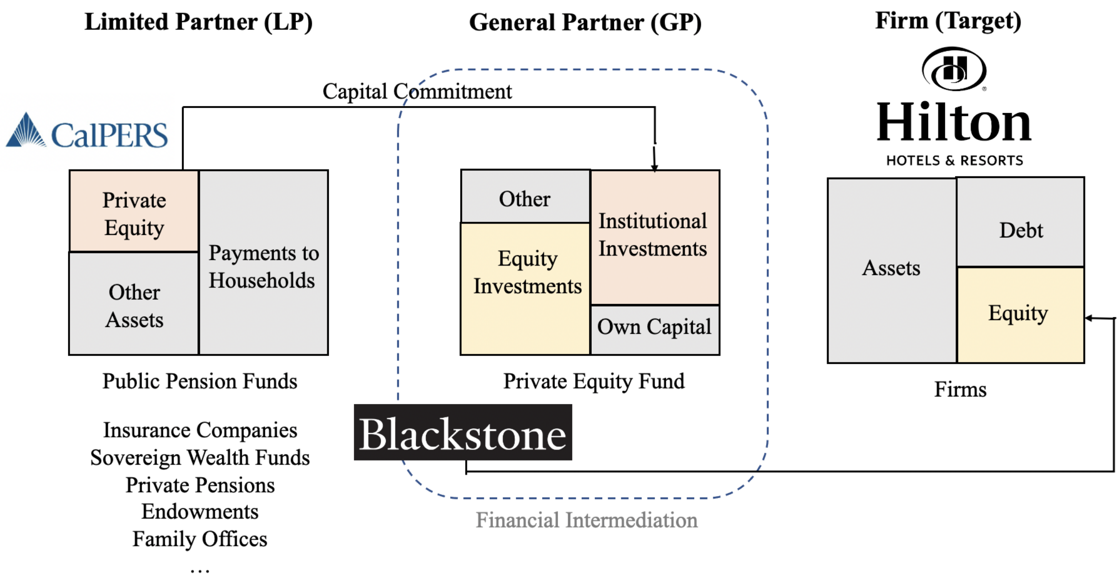
In Panel C, I split firms by a measure of private equity fund family size. This measure is proxied by the market value of fund family, including the book and market value of investments. The fund size measure can be thought of as the private equity quality, borrowing from the mutual fund literature which shows manager skill is visible in the cross-sectional distribution of fund size (Berk and van Binsbergen (2015)). Firms financed by the bottom 25th percentile of fund family size have an average $391,000 in labor productivity, and those financed by the top 75th percentile generate $407,600 per employee on average. These statistics suggest significant variation in performance at targets, based on investor categories.

2.2 Institutional Background

Private equity as a form of financial intermediation has gained prominence over the past 20 years. Figure 4 depicts a schematic institutional structure. Capital flows from institutional investors, also called limited partners or "LPs" (left) to firms or "targets" (right). Institutional investors like public pension funds, insurance companies, sovereign wealth funds, private pensions, endowments, family offices, etc. are suppliers of capital. The intermediary sector consists of agents providing financing to firms. A firm (for e.g., Hilton) generally faces a menu of options to obtain financing: traditional banks, private equity funds (sometimes also referred as non-banks), corporate bonds, public equities, and internal financing. The focus of this paper is the private equity fund family or general partner ("GP", for e.g. Blackstone Group), and its constituent funds (for e.g. Blackstone Capital Partners VI).

Private equity funds obtain majority of their capital for deals from investors, approximately 95%, while the rest is financed by themselves. The contractual agreement, called the Limited Partnership Agreement (LPA), states contract details between investors and funds including

Figure 4. Connection between pension funds, financial intermediaries and firms



Notes: Figure depicts transfer of capital in private capital markets from the supplier (investor, LP on the left hand side) to the receiver (firm, target on the right side) via the intermediary (PE fund, GP in the middle).

the return and fees. Fees includes a management fee and performance fee, and are negotiated between the investor and fund.

Institutional investors commit capital to private equity funds. This capital is generally committed at inception of the fund. Over time, private equity funds call portions of the committed capital, and investors make the contributions. On receiving the capital, private equity funds invest in target firms, earn cash flows from operations or from disposition of investments, and make distributions to their investors. These distributions are net of management and performance fees. The returns net of fees follow a waterfall structure where the private equity fund's portion of returns (or "carried interest") becomes larger as performance hurdles are reached. Investors are residual claimants on the net asset value of the fund.

3 Pension Funds' Investments in Private Equity

3.1 Matching of Underfunded Pensions and PE Funds

Having shown that public pensions' allocations to alternative assets have increased drastically, and in recent times the most underfunded pensions have become a major contributor to private equity capital, in this section I discuss the individual portfolio investments of public pensions.

I split the private equity fund families into deciles based on the assets under management of the fund. Following the literature on mutual funds which shows that managerial skill is reflected in the cross-sectional distribution of fund size and assets under management (Berk and van Binsbergen (2015)), this is indicative of the quality of the private equity fund family more broadly. I also find evidence for smaller fund families with less assets, having less number of private equity funds, and less connections – all measures which are ultimately correlated with the deals financed by these funds. This is a useful measure, especially for non-traded fund families.

I use two measures of private equity fund family size: (1) book value measure, which is the sum of total size of existing private equity funds within the family for each year, and (2) market based measure, which is the sum of book value of capital committed by investors to private equity, additional market value of private equity investments, and capital yet to be called ("dry powder"), covering all asset classes[10]. I use the year of inception and lifespan of the fund to determine years of existence for each private equity fund. When I do not observe the lifespan, I take the median value of 10 years (motivated by Kaplan and Strömberg (2009)). The first measure allows me to track fund family size over time, while the second measure allows me to incorporate the performance of funds. Higher private equity book value assets represents bigger scale and better quality within the private equity industry.

Investors maintain the same split of most underfunded pensions, medium underfunded, least underfunded, and other investors. I focus on public pensions to highlight differences across public pensions in their allocation to different private equity fund families. I consider underfunded ratios of pensions at the time of capital commitment to a private equity fund. Post commitment to a fund, the capital is locked in the investment for 5-7 years. The year of capital commitment is taken as the inception year of the private equity fund. This is reasonable as a fund receives most of its capital commitments when the fund is set up.[11] Consequently, I split public pensions based on their underfunded ratios for each year separately.

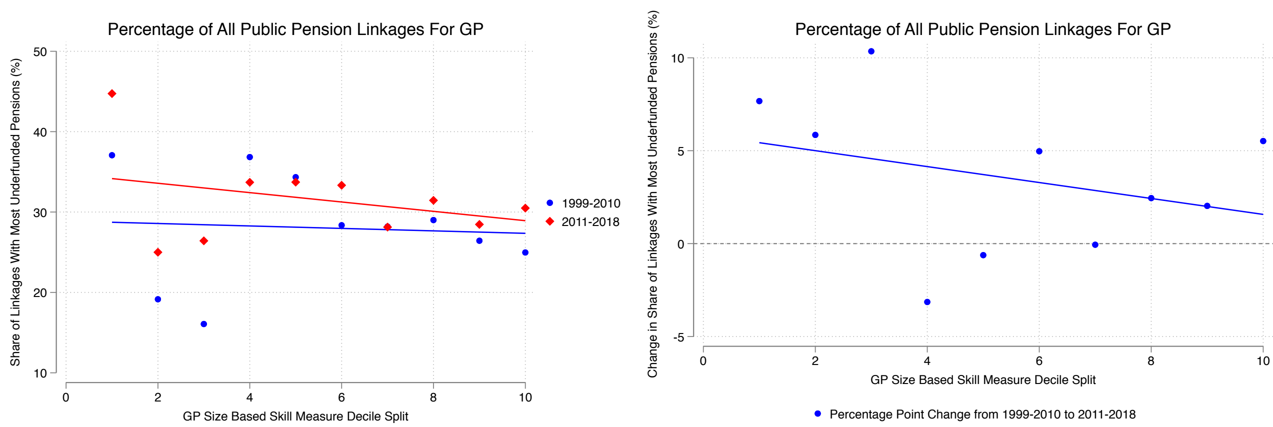
I count investment linkages between investors and private equity fund families based on their characteristics. Investment linkages represents the number of times an investor invests in a fund family within a given time period. Figure 5 shows percent of investment linkages between the most underfunded pensions and fund families in the two time periods: the

[10]This is reported directly by the fund family. It is a complicated measure as it covers market value of non-traded private assets. This is only available as of the latest date reported by the family ranging from 2019 to 2022 depending on the GP. Hence, I also use the book value measure.

[11]Supported by interviews with industry professionals and Preqin data provider.

first half of 2000s, 1999 to 2010 (blue), and the second half of 2000s, 2011 to 2018 (red). Panel B shows the change in assortative matching between the two periods. Panel A shows amongst all links with public pensions, the smallest fund family had 44.7% links with the most underfunded category in 2011-2018, which is 7.7% higher than in 1999-2010. This increase is substantial as private equity investments are long-term, sticky, and relationship based.

Figure 5. Percent of Investment Linkages Between Most Underfunded Pensions and Private Equity Fund Families Across Time



Notes: This figure counts connections of invesment links between the most underfunded public pensions and private equity fund families for two time periods: (1) 1999-2010 and (2) 2011-2018. The year of commitment is the vintage year of the private equity fund. Data are sourced from Preqin.

There are two main takeaways. First, the slope between the percentage of links with the most underfunded category and the fund family size measure is negative in 2011 to 2018, the second half of the sample (red line). This shows that smaller private equity fund families match with more underfunded pensions. Second, the slope of the change in percentage of investment links between the two periods, 1999 to 2010 and 2011 to 2018 is negative. Steepening of the curve shows that the increase in matches with the most underfunded pensions is higher for smaller fund families.[12] The bigger fund families such as Blackstone Group, Kohlberg Kravis Roberts & Co. (KKR), and Goldman Sachs Alternatives (AIMS) Group have connections with all types of investors. Small fund families like Wicks Group with a total 4 funds since 1989, had \$15 mn. capital commitments from Philadelphia Board of Pensions and Retirement in 2005, and combined \$65 mn. capital from Philadelphia Board of Pensions, Illinois State Board of Investment and Oklahoma Teachers Retirement System in its 2012 fund. This documents assortative matching between the most underfunded public pensions and the smallest fund families.

[12]The result is consistent across fund family splits. As a robustness, I split fund families into 20 cateogories and find similar evidence of steepening of the curve.

Formally, I regress the private equity fund family size on underfunded positions of public pensions in the year of capital commitment.

$$y_{pst|p\in j} = \gamma_t + \beta \cdot \text{Underfunded Ratio}_{pst} + \text{Controls} + \epsilon_{pst} \tag{1}$$

where, p is public pension, s is state, j is fund family, and t is year of capital commitment. y is total size (in logarithmic terms) of the fund family in year t, which is the sum of size of all its component funds existing in that year.[13] For each pension, I take the average size across fund families in which public pensions invest for each year, and aggregate to a pension fund-capital commitment year level for estimating equation 1.

I control for public pension characteristics: assets, average past 3 year allocations to different asset classes, fund benchmark returns to account for fundamentals other than underfunded ratios of pensions. To account for concerns of more underfunded pensions matching with different types of private equity funds rather than smaller funds, I control for multiple fund characteristics like industry focus of the fund, strategy – for instance, balanced, growth, special situations, investment region focus, and domicile of the fund. Additionally, I control for fund vintage γ_t to account for changes over time. I do not include pension fixed effects as the matching is across public pensions and private equity funds.

Table 2. More Underfunded Pensions Match with Smaller Private Equity Funds, 1997-2018

	(1) GP Quality	(2) GP Quality	(3) GP Quality	(4) GP Quality
Underfunded Ratio	-0.431**	-0.614***	-0.534***	-0.616***
	(0.176)	(0.181)	(0.193)	(0.198)
LP AUM	Yes	Yes	Yes	Yes
Past Asset Allocations			Yes	Yes
Fund Benchmark Returns				Yes
Fund Industry Focus				Yes
Fund Strategy				Yes
Fund Region Focus				Yes
Fund Domicile				Yes
Vintage Year FE	Yes	Yes	Yes	Yes
Positive PE Allocation		Yes	Yes	Yes
Regression Type	OLS	OLS	OLS	OLS
Observations	1455	1244	1084	850
Adjusted R squared	0.298	0.311	0.280	0.461
Depedent Variable Mean	8.681	8.695	8.828	8.896
Depedent Variable Std	1.209	1.202	1.116	1.121

Notes: Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column 4 of table 2 shows estimates for the most saturated specification of pension fund

[13] Details of the measure defined in Section B.2.

and private equity fund controls. More underfunded pensions allocate capital to smaller private equity funds within their private equity allocations. Coefficient for underfunded ratio is -0.62 ($t = -3.17$), and is statistically significant at 1% level. The estimate is also economically significant. For a one-standard-deviation increase in underfunded ratio (17.5%), logarithmic size decreases by 0.11 log points. In levels, the average private equity fund size is $7,274 mn., and 0.11 log point change corresponds to a -10.3% change.[14]. The 10.3% decrease in size of the private equity fund for a one-standard-deviation increase in underfunded positions is similar in magnitude to the 7.7% increase in the proportion of financing received by the smaller private equity funds from the most underfunded pensions (figure 5). Similarity of magnitudes across the two fund size measures lends support for comparability of the quality metrics. Additionally, studying changes in capital flow from both the private equity fund and public pension perspective confirms the matching story.

3.2 More Underfunded Pensions Realize Lower PE Returns

For years 1997 onwards, the most underfunded pension category has an average underfunding ratio of 38.4%, with the least underfunded pension being 4.4%. To cover up their shortfall of underfunded positions, pensions would want high returns. In this section, I study the ex-post returns from investments in private equity.

I estimate specification 1 with y_{pst} being total realized private equity returns for pension fund p in time t. I have pension fund characteristic controls as before, but not for private equity funds as these regressions are solely at the pension fund-year level. I include pension fund fixed effects. The regressions estimate how private equity returns respond to pensions' underfunded positions. Table 3 shows that within private equity more underfunded pensions receive lower *total realized returns* post controlling for public pension characteristics of size, past average asset allocations, and investment consultants reflecting public pension mandates. Average underfunding ratio is 23.3%. A one-standard-deviation (19.9%) increase in underfunded positions, decreases average PE returns by 2.7 percentage points (23.0% standardized change).

Together with the results on private equity fund size, this suggests that more underfunded public pensions are allocating capital to smaller funds which also give them lower returns relative to the least underfunded public pensions. Lower total private equity returns earned

[14] Average logarithmic size is 8.89 ($\equiv$ \$7,274 mn). With a coefficient of -0.62, change in log points is $-0.62 \times 17.5\% = 0.11$ log points change in the dependent variable. The average dependent variable in log terms along with the effect of underfunded positions is $8.89 - 0.11 = 8.78$ ($\equiv$ \$6,525 mn.). In level terms, the change in size of the fund is -$749 mn., which is a -10.3% change.

by the more underfunded pensions provides circumstantial evidence in support the story of smaller funds being of lower quality, interpreted more broadly.

Table 3. Correlation Between Public Pensions Underfunded Positions and Private Equity Returns, 2001-2021

	(1) PE Ret(%)	(2) PE Ret(%)	(3) PE Ret(%)	(4) PE Ret(%)
Underfunded Ratio	-0.104***	-0.103***	-0.102***	-0.136***
	(0.0315)	(0.0314)	(0.0314)	(0.0361)
LP AUM	Yes	Yes	Yes	Yes
Current PE Allocation		Yes		
Current Alternatives Allocation			Yes	
Past Asset Allocation				Yes
Investment Consultant Dummies				Yes
Pension Fund FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1988	1988	1988	1786
Adjusted R Squared	0.650	0.650	0.650	0.654
Dependent Variable Mean	0.115	0.115	0.115	0.119
Dependent Variable Std	0.153	0.153	0.153	0.148

Notes: Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The result encompasses a couple of possible explanations. The big private equity funds get the best deals while the smaller funds get the worse ones. This is plausible as the top 30 private equity funds have greater than 50% market share. A second possibility is that the small funds have smaller teams to manage firms, and are not able to get high returns from investments. Third, small funds are new and the existing big funds have established relationships with investors. Fourth, small funds might be showing high return expectations but are not able to meet them. I do not observe return expectations at the fund level as these would be included in Limited Partnership Agreements between investors and funds which are confidential. I see evidence in support of these mechanisms but given the data available, I am not able to disentagle these.

4 Evaluating Private Equity Target Firms

To look further into the public pension investments in private equity, next I study the investments underlying private equity transactions supported by public pensions. As most of the firms are private and undergo structural changes during private equity transactions, I turn to the Census Bureau micro data which has the most comprehensive information on such firms. I study the evolution of target firms pre- and post-buyout transactions.

$$y_{it} = \alpha_t + \alpha_0 \text{Post Buyout}_{it} + \gamma \text{LFIRM}_i + \text{Fixed Effects} + \epsilon_{it} \tag{2}$$

y_{it} is the outcome variable in growth rates for firm i at time t. These are one-year "DHS" growth rates (Davis, Haltiwanger and Schuh (1996)) from $t-1$ to t for firm i, where $y_{it} = \Big(Y_{it} - Y_{it-1}\Big)/(X_{it})$ and $X_{it} = 0.5 \times \Big(Y_{it-1} + Y_{it}\Big)$.[15] Post Buyout is a dummy which takes the value 1 for the year corresponding to the buyout and after. α_0 is the coefficient of interest measuring the effects of outcome variables post buyout activity. Following earlier literature (Davis et al. (2014), Davis et al. (2019)), I include year, industry, size, age, and type of unit fixed effects, to account for potential differences across entities and industries.

Table 4 shows estimated coefficients α_0 for equation 2 for year over year growth rates. Employment changes by -8.4% per year, revenue by -8.6%, with an insignificant -0.2% change in labor productivity. Figure **??** shows the dynamic estimates five years pre- and post-buyout.[16]

4.1 Target Firms Predominantly Backed by Public Pensions

Figure 1 shows allocation to alternatives by public pensions have increased from 8% in 2001 to 27% in 2020. Further, the share of capital committed by the most underfunded public pensions has increased. I combine the pension assets and liabilities with the LP commitment amounts, and split pension funds into terciles based on their underfunded ratios at the time of capital commitment.

Figure 2 shows the three year moving average of capital committment shares by the most underfunded pension tercile. The blue line shows that the most underfunded pensions contributed 15.6% of all capital to PE funds in 2018, which is 10 percentage points higher than in 2001. Out of the total capital committed by all public pensions, the most underfunded group contributed 9.6% in 2001 and 29.0% in 2018. This corresponds to a commitment amount of \$919 mn. in 2001 and \$14 bn. in 2018. The increasing importance of private equity investments financed by the most underfunded public pensions over time, motivates

[15] I calculate growth rates of revenue and total payroll in 2020 U.S. dollars. Revenue is deflated by the U.S. GDP Price Deflator Series, link: https://fred.stlouisfed.org/series/USAGDPDEFQISMEI. Pay is deflated by the Consumer Price Index for All Urban Consumers (CPI-U).

[16] Additional robustness checks (not reported) include specifications with year and industry fixed effects; year and firm size fixed effects; year and firm age fixed effects; year and type of unit fixed effects; year, industry and firm size fixed effects; industry $\times$ year, firm size, age, and type fixed effects. Results remain unchanged.

Table 4. Event Study Estimated Coefficients of Post Buyout, Private Equity Deals 1997-2018

Dependent Variable:	Emp g (1)	Pay g (2)	Rev g (3)	Rev g -Emp g (4)
Post Buyout	-0.084^{***}	-0.075^{***}	-0.086^{***}	-0.002
	(0.016)	(0.016)	(0.011)	(0.013)
Year FE	Y	Y	Y	Y
Firm Size FE	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Type of Unit FE	Y	Y	Y	Y
Lagged Firm g	Y	Y	Y	Y
Weighted Emp t_0	Y	Y	Y	Y
Observations	70,000	70,000	70,000	70,000
Adjusted R^2	0.183	0.193	0.132	0.015
Dependent Variable Mean	0.023	0.028	0.026	0.003

Notes: The table displays coefficients α_0 of the event study specification 2:

$$y_{it} = \alpha_t + \alpha_0 \text{Post Buyout}_{it} + \gamma \text{LFIRM}_{\ i} + \text{Fixed Effects} + \epsilon_{it}$$

Standard errors are clustered at the firm level. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

the study of target firms ultimately supported by underfunded public pension capital in the cross-section and time-series.

In my final sample, public pensions consist of 31.3% of all investors, private pensions are 22%, insurance companies 11%, foundations, endowments, and soverign wealth funds are 17.6%, and the rest 18.2% are family offices, funds of funds, asset managers, banks etc. I have capital contributions by investors to individual private equity funds in 38.1% of the cases. This is the most sensitive information between the investor and the private equity fund. While this is a small sample, Brown et al. (2015) documents the representativeness of this dataset across databases, showing this is the most comprehensive existing source. Amongst the contributors, public pensions contribute 67.8% and insurance companies 13.2%. U.S. public pension funds is the largest group amongst public pensions, accounting for 95% of capital contributions. Public pension funds emerge as the dominant group of investors in private equity.

On average, 20 investors are involved in financing a deal though commingled PE funds. Targets are bought by commingled private equity funds, where capital from multiple investors is pooled together. As a first step, I classify the dominant investor in each deal based on the capital commitment amount, i.e., a deal is classified as a public pension fund supported deal if the maximum dollars in the deal flow are from public pensions. I split targets between those supported by public pensions, and those supported by "other investors" which are insurance companies, sovereign wealth funds, family offices etc.

The main factor distinguishing public pension funds from other investors is their underfunded positions. To identify firms supported by the most underfunded pensions, I calculate underfunded ratios at the target firm level i, weighted by the capital committed by the individual pension fund p to firm i via private equity fund j with a fund family, representing the public pension presence in the deal,

$$\phi_i = \frac{\sum_{pji} w_{pji} \cdot \text{Underfunded Ratio}_{p,p\in ji}}{\sum_{pji} w_{pji}} \tag{3}$$

I split ϕ_i into terciles to estimate the following specification,

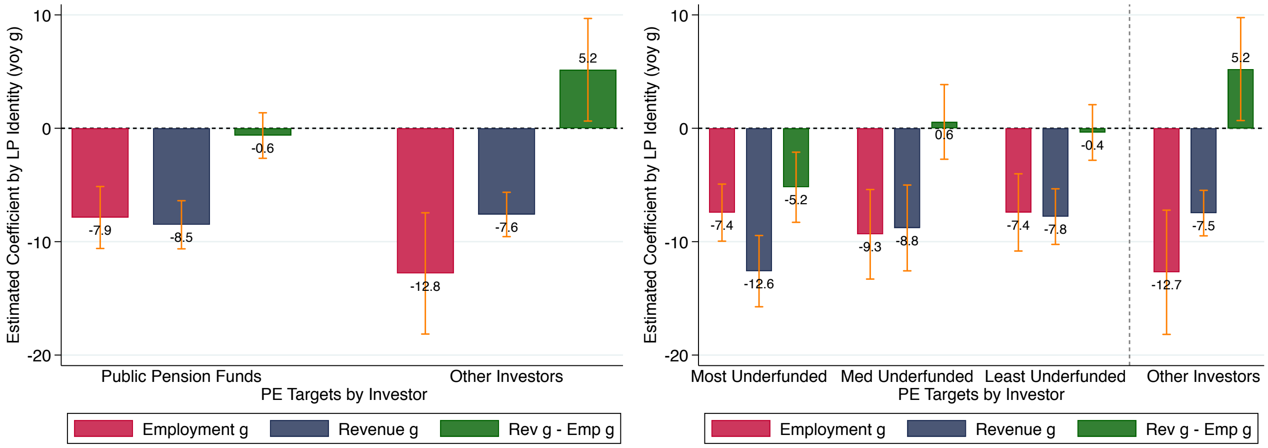
$$y_{it} = \alpha_t + \alpha_0 \text{Post}_{it} + \sum_{r=1}^{3} \beta^r \left(\text{Post}_{it} \times \mathbb{I}_i^{UF^r} \right) + \gamma \text{LFIRM}_i + \text{Fixed Effects} + \epsilon_{it} \tag{4}$$

This is similar to specification 2 with an additional interaction term of Post_{it} with $\mathbb{I}_i^{UF^r}$, where $\mathbb{I}_i^{UF^r}$ is a dummy which takes the value 1 for targets supported by public pensions in underfunded tercile r. Post_{it} captures the "other investor" category. I use the fully saturated specification controlling for industry, size, age, and type of the firm in addition to year fixed effects, to compare very similar target firms but differing by the type of investor in the deal. I also control for pre-buyout growth to account for pre-buyout trends of the firm.

Figure 6 panel A shows the estimated post buyout coefficients for employment, revenue, and labor productivity growth rates for firms supported predominantly by public pensions (3,900 firms), and those by other investors (1,300 firms). Deals financed by other investors experience a +5.2% change in labor productivity per year, whereas those financed by public pensions face a -0.6% insignificant yearly productivity change. This points to specialness of public pensions as investors in financing firms. Panel B splits the public pension supported firms into terciles based on underfunded ratio of pensions. Within public pension supported firms, firms supported by the most underfunded pensions (1,200 firms) face a -5.2% productivity change on a yearly basis.

Tables 8 and 9 show the incremental differences for public pensions and underfunded categories as compared to other investors are large and significant. Firms supported by the most underfunded pensions experience a -10.4% productivity change relative to the other investor firms. In the aggregate, there are insignificant changes (+0.3% yoy) in labor productivity post buyout. These results suggest there is substantial heterogeneity in target firms by investor characteristics. It is important to note that pension funds do not cause

Figure 6. Estimates of Post Buyout × Investor Type, Private Equity Deals 1997-2018



(A) Public Pensions vs. Other Investors **(B)** Underfunded Terciles vs. Other Investors

Notes: Panel A plots coefficients for equation 4 with two categories: other investors and public pension funds supported firms. Panel B plots coefficients from four categories in equation 4: other investors, most underfunded, medium underfunded, and least underfunded public pension supported firms. These are total coefficient estimates; bars represent 90% confidence intervals.

Figure 7. Estimates of Post Buyout × Investor Type, Deals Pre and Post 2011

(A) Pre-2011 **(B)** Post-2011

Notes: Panel A plots coefficients from four categories in equation 4: other investors, most underfunded, medium underfunded, and least underfunded public pension supported firms pre-2011, while Panel B plots post-2011 estimates. These are total coefficient estimates; bars represent 90% confidence intervals.

target firms to perform poorly as they do not have direct contact with targets. The target firms evolve differently based on the type of investor, due to the private equity fund families underfunded pensions match with.

This evidence holds for different splits of the data, for example, quartile splits based on underfunded positions of pensions in figure A.25, and different aggregation methods. For instance, when studying only public pensions and taking the weighted average of underfunded ratios across public pensions, using capital commitments as weights instead of first identifying the dominant investor in each deal, I find similar results – the most underfunded public pension supported firms face a -5.5% to -5.3% change in labor productivity per year (figure 17, table 10). To account for macroeconomic conditions, I residualize underfunded ratios with local region fixed effects and 10 year interest rates, and find similar results (figure 18).

Motivated by the change in assortative matching between public pensions and private equity funds discussed in Section 3, I study the cross-sectional differences at target firms by investor type over time. Figure 7 shows coefficient estimates by investor types over two time horizons, pre-2011 and post-2011. While this mostly a post financial crisis change due to increase in underfunded positions of pensions, it takes a couple of years for private equity funds to raise capital. The cross-sectional differences in labor productivity between target firms financed by different investors is insignificant in the earlier period, while the differences are larger in the second half. This emphasizes that it is the second half of the period which observes target firms receiving capital from underfunded public pensions experiencing negative productivity changes. It would have been ideal to observe cost measures at firms as well. I only observe total wages in the Census data, and find that similar results after accounting for that.

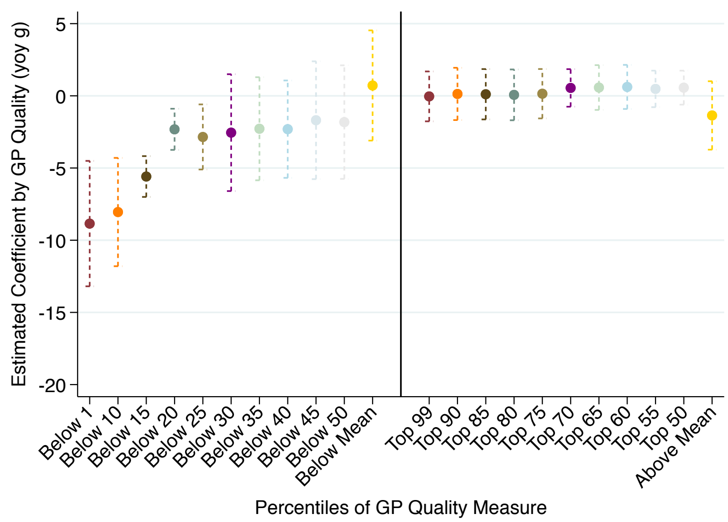
4.2 Target Firms by Private Equity Fund Families

Investors provide capital to private equity funds which ultimately invest in target firms. Private equity funds are active managers directly engaging in operations of target firms, while investors are passive and only provide capital to private equity funds. As small private equity fund families received more capital from the most underfunded pensions in the second half of the sample period, I study differences in target firms based on fund family size.

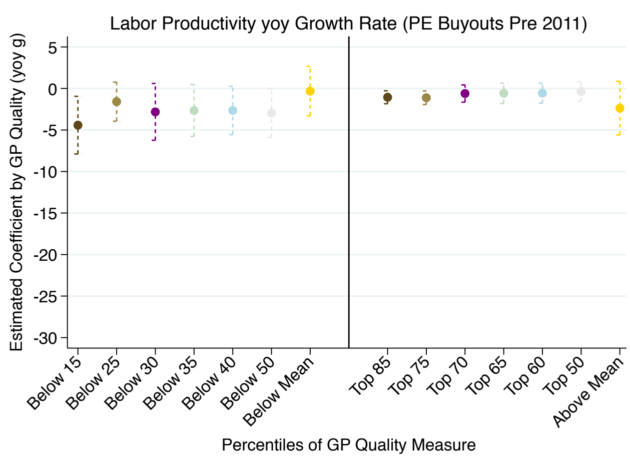
I aggregate fund family size based quality measures at the target firm level. I weight fund family characteristics by the number of funds within a family involved in a deal. Rankings across fund families are persistent over time and across the two measures of size.

I estimate specification 4 with varying splits of firms based on private equity fund family size distribution. Instead of Post_{it} interacted with $\mathbb{I}_i^{UF^r}$, I now estimate coefficients for Post_{it} interacted with $\mathbb{I}_i^{FF^x}$. $\mathbb{I}_i^{FF^x}$ is an indicator variable which takes the value 1 for firms financed by fund families of size less than or equal to xth percentile. Similar to above, I am comparing outcomes at target firms post buyout within granular 22 two-digit NAICS industry codes, 5 firm age and 12 firm size buckets, and same type of firm – multi or single establishment, and the year of buyout, but differing by the fund family size supporting the deal. Inclusion of granular characteristics of targets allow me to get close to comparing similar firms undergoing a private equity transaction.

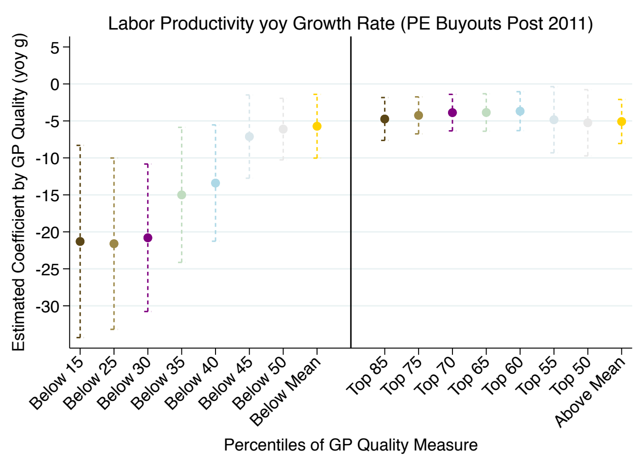
Figure 8. Labor Productivity g Estimates of Post Buyout $\times$ Private Equity Fund Family Size Percentile, Private Equity Deals 1997-2018



(A) 1997-2018



(B) Pre-2011



(C) Post-2011

Notes: The figure shows labor productivity yoy growth rate estimates from equation 4, where $\left(\text{Post}_{it} \times \mathbb{I}_i^{UF^r}\right)$ is substituted with $\left(\text{Post}_{it} \times \mathbb{I}_i^{FF^x}\right)$. $\mathbb{I}_i^{FF^x}$ is an indicator variable which takes the value 1 for target firms financed by fund families of size less than or equal to xth percentile. I estimate the regression for different percentiles: $x = 1, 10, 15, 20, 25, 30, 35, 40, 45, 50$, mean, where each color shows estimates from a different percentile cut. Panel A shows considers deals from 1997 to 2018, panel B considers deals pre-2011, and panel C for post-2011. These are total coefficient estimates for each category. Bars represent 90% confidence intervals.

Figure 8 Panel A shows firms supported by the smallest fund families experience greatest decreases in productivity. For instance, firms supported by the bottom 20th percentile experience −2.3% year over year labor productivity changes, those supported by the bottom 15th percentile experience −5.6% yearly changes, and those supported by the bottom 10th percentile face −8.1% yearly changes. I plot estimates for different percentiles, which shows that the trend holds across different percentile distributions (estimates from one regression are in the same color). These are total estimates of coefficients for one category. I also show that the incremental estimates are statistically and significantly different across categories in the same regression.

Panels B and C show the cross-sectional differences in labor productivity estimates for target firms financed by small private equity fund families as compared to the large ones are stronger in the second half of the sample. These inferences are consistent with the assortative matching between the most underfunded pensions and smaller funds, and large labor productivity losses at target firms predominantly financed by the most underfunded pensions, both in the later half of the sample.

As private equity funds have an active role in determining capital allocation towards deals. It is possible that small funds are not good at managing firms, because they don't have the expertise. I account for observable characteristics of firms to compare very similar firms differing by the fund family size which is financing the deal. On the other hand, it is also possible that smaller funds get worse deals. With the influx of capital from underfunded pensions, more private equity funds are being supported at the margin with only limited good projects. I am unable to observe the information set of private equity funds during deal selection, and hence cannot disentangle these two possibilities beyond controlling for observable characteristics.

5 Identifying Desperate Capital Using Public Unions

As pension funds use their average return of average returns on assets to discount their future liabilities, it is in their best accounting interests to target high returns. Private equity is a high return asset class, which is not necessarily marked to market. This gives public pensions an incentive to swing for the fences.

I study the distributions of realized private equity returns of U.S. public pensions from the same sample period as the private equity deals, before and after 2011. I maintain the split of public pension funds by their underfunded positions based on the year before their investments. Figure 9 shows the distributions of returns for the most and the least underfunded pensions are not very substantially different in the pre-2011 period. However, the distribution of returns to the most underfunded pensions have thicker tails in the post period, relative to the distributions of the least underfunded pensions in the post period and the most underfunded pensions in the pre period. This suggests that the most underfunded gambling for ressurection. In the next section, I will discuss an instrument for underfunded positions to support this channel.

Figure 9. Return Distribution of Public Pensions by Underfunded Positions

(A) Pre-2011 **(B)** Post-2011

Notes: The figure shows the return distribution of public pension funds by their underfunded positions one year before the investments. Panel A shows returns pre-2011, and Panel B shows returns for post-2011. Data are sourced from Public Pensions Database and FOIA requests.

5.1 Instrument for Underfunded Positions

Post the Great Financial Crisis (GFC) in 2008, the funded ratio did not recover even though the stock market bounced back. As of 2020, public pensions are funded at 72.4%, i.e., for every \$100 of liabilities, a public pension fund only has \$72.4 in assets (figure 13). To cleanly identify the effects of underfunded positions of pensions, i.e., desperation, I want to rule out unobservable characteristics of investors which might be correlated with underfunded positions and private equity fund size. One possible confounder is investor skill. Underfunded pensions might also be low skilled which might lead them to mismanage capital resulting in higher underfunded ratios, and higher allocation to smaller lower quality private equity funds. Despite accounting for observed public pension differences via controls, skill might be unobserved. To show a causal link between underfunded positions of pensions and their allocation to individual private equity funds, I use exogenous variation in underfunded ratios which only affects the liability side.

I introduce a novel instrument for public pension underfunded positions, by exploiting cross-sectional variation in unionization amongst public employees in a state-year. Public unionization rate, also known as union density is reported by the Current Population Survey (CPS). As part of the CPS conducted by the U.S. Bureau of Labor Statistics (BLS), survey respondents are asked: 1. "Are you a member of a union?". Empirically,

$$\text{Union Density } (\%)_{st} = \frac{\text{Number of members}_{st}}{\text{Number of Government Employees}_{st}} \tag{5}$$

There is a wide cross-sectional variation in public unionization rates across states. Figure 19 shows variation in public union density across all U.S. states over time. While North Carolina had a union density of 6.6% in 2018, New York had 66.6% of its public workers as part of a union.

This instrument is valid under two identifying assumptions. First, the relevance condition, i.e., public unionization affects underfunded ratios of public pensions. Intuitively, this makes sense as public workers, such as, teachers, firemen, and state employees heavily rely on public pensions for their pay, and higher unionization amongst public workers leads to higher monetary and non-monetary benefits which strains funded ratios of public pensions.[17] Freeman (1983) shows unions increase pension coverage. Figure 20 shows evidence of a +17.3% significant correlation between underfunded public pensions and one year lagged public union density for 2011 to 2018.[18]

Second, the exogeneity condition should hold, i.e., public unionization rates affects investments by pensions to specific private equity funds and ultimately private equity returns only through pensions' underfunded positions. This is plausible as portfolio allocation decisions are made by an investment committee which is generally separate from other operations of pensions. Further, the instrument of unionization rate is at the state-year level, and not at the pension-year level. Hence, it is reasonable to assume that the unionization rate is taken as given by the public pension. To alleviate reverse causality concerns, higher underfunded positions can lead to higher union representation, I use union density from one year before relative to underfunded ratio.

[17] For instance, https://uniontrack.com/blog/unions-retirement-benefits mention ways unions impact pensions.

[18] Correlation is +6.3% and significant for 1997-2018.

5.2 Empirical Methodology and Results

Formally, the first and second stage of the empirical specification are shown in equations 6 and 7 respectively.

$$\text{Underfunded Ratio}_{pst} = \alpha_t + \beta \cdot \text{Union Density } (\%)_{st-1} + \text{Controls} + \epsilon_{pst} \tag{6}$$

$$y_{pst|p\in j} = \gamma_t + \beta_{IV} \cdot \widehat{\text{Underfunded}} \text{ Ratio}_{pst} + \text{Controls} + \epsilon_{pst} \tag{7}$$

As before, p stands for pension fund, s is state, j is private equity fund, and t is year. $y_{pst|p\in j}$ is the size of a private equity fund a public pension commits capital to in time t. y_{pst} will also measure the total realized private equity returns for a public pension in time t. The controls follow the most saturated specification of the OLS for the respective dependent variables.

Table 5 reproduces the OLS from Column (4) in tables 2 and 3, and presents the first and second stage IV results. The first three columns correspond to private equity fund size, and the last three show results for realized private equity returns. The first stage coefficient of interest is β, and expected to be positive. For private equity fund size, the coefficient on "Lag 1 Year Union Density" is positive and highly significant ($\beta = 0.164$, $t = 5.44$). The effect is economically significant, as a one-standard-deviation (18.6%) increase in public unionization rates, increases underfunded positions by $0.164 \times 18.6\% = 3.1$ percentage points. With an average underfunded ratio of 23.1%, this corresponds to a 13.2% percentage change. Accordingly, higher unionized states have pension plans with higher underfunded ratios.

It is important for the IV to be "strong", i.e., the exogenous variable – one year lagged public union density to be strongly correlated with the endogenous variable – underfunded positions of public pensions, especially for IV estimation in finite samples. In column (1), the F statistic for the null that $\beta = 0$ is 29.6, which is greater than the rule of thumb ($F \geq 10$) proposed by Staiger and Stock (1997), and the 10% critical value in Table 5.2 of Stock and Yogo (2005). Similarly, in column (4), the F statistic is 24.1 ($t = 4.91$), which statisfies both conditions of a strong IV. Thus, weak instrument is unlikely to be a concern.

The 2SLS coefficients are in the same direction as the OLS and statistically significant. The OLS is biased downward as the 2SLS coefficient (-2.455) is higher in magnitude than the OLS coefficient (-0.592). The coefficients are not statistically significantly different from each other at 10% level. This is true for both private equity fund size and return regressions. The standard errors are bound to be large in a small samples with multiple dummies and controls. This lends support to the fact that underfunded ratios is the driver behind these

Table 5. Instrumental Variable Results for Private Equity Fund Size and Returns

	Private Equity Fund Size			Realized Private Equity Returns		
	(1) Underfunded Ratio	(2) Log(GP Size)	(3) Log(GP Size)	(4) Underfunded Ratio	(5) PE Ret(%)	(6) PE Ret(%)
Lag 1 Year Union Density	0.164***			0.367***		
	(0.0302)			(0.0748)		
Underfunded Ratio		-0.592***	-2.455**		-0.136***	-0.497**
		(0.202)	(1.089)		(0.0361)	(0.240)
Assets	Yes	Yes	Yes	Yes	Yes	Yes
Average Past Asset Allocations	Yes	Yes	Yes	Yes	Yes	Yes
Fund Benchmark Returns	Yes	Yes	Yes			
Investment Consultant Dummies				Yes	Yes	Yes
Fund Industry Focus Dummies	Yes	Yes	Yes			
Fund Strategy Dummies	Yes	Yes	Yes			
Fund Region Focus Dummies	Yes	Yes	Yes			
Fund Domicile Dummies	Yes	Yes	Yes			
Vintage Year FE	Yes	Yes	Yes			
Pension Fund FE				Yes	Yes	Yes
Year FE				Yes	Yes	Yes
Positive PE Allocation	Yes	Yes	Yes			
Regression Type	First Stage	OLS	Second Stage	First Stage	OLS	Second Stage
Observations	850	850	850	1786	1786	1786
Adjusted R Squared	0.243	0.449	0.215	0.899	0.654	-0.140
Depedent Variable Mean	0.231	8.896	8.896	0.223	0.119	0.119
Depedent Variable Std	0.175	1.122	1.122	0.199	0.148	0.148

Columns (1)-(3) present results for GP Quality from specifications 6, 1, and 7. Columns (4)-(6) show results for Realized PE Returns. Average past asset allocations is average of past three year equity allocation, fixed income, and private equity allocations. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

results, i.e., desparate capital. I get similar results in economic and statistical significance when limiting the sample to pensions and funds supporting the firms, which I am able to match to the Census micro-data.

To futher substantiate the cause for underfunded positions, I estimate specification 4 by splitting targets into terciles of state public union density of the corresponding public pensions supporting the target. Column (1) of table 6 reproduces estimates from equation 4, and column (2) provides estimates from the union density split. Using underfunded positions, I find that the change in labor productivity at targets post buyout is -10.4% per year relative to the other investor supported firms. When using union density, the effect is -7.0%.

Intuitively, estimates in the same direction and of similar magnitude from both approaches imply that the sorting of targets into terciles using underfunded positions and union density has a good match. This confirms that it is the underfunded positions of pensions, which is the reason for pensions to end up with smaller and low quality private equity funds, which ultimately gives them lower private equity returns relative to the less underfunded pensions. The small private equity funds then invest in firms which do worse in terms of labor productivity post the private equity deal.

Table 6. Post Buyout Labor Productivity Effects by Investor Split Using Union Density

Investor Split	Rev g-Emp g Underfunded Ratio (1)	Rev g-Emp g Union Density (2)
Post Buyout (Base: Other Investors)	0.0522*	0.0497*
	(0.0276)	(0.0277)
Post Buyout × Most Underfunded Pensions	−0.1040***	−0.0696**
	(0.0301)	(0.0286)
Post Buyout × Medium Underfunded Pensions	−0.0466	−0.0614**
	(0.0295)	(0.0289)
Post Buyout × Least Underfunded Pensions	−0.0559**	−0.0531*
	(0.0260)	(0.0281)
Observations	53,500	53,500
Adjusted R^2	0.0203	0.0194
Dependent Variable Mean	0.0003	0.0003
Year FE	Y	Y
Firm Size FE	Y	Y
Firm Age FE	Y	Y
Industry FE	Y	Y
Type of Unit FE	Y	Y
Lagged Firm g	Y	Y
Weighted Emp t_0	Y	Y

Notes: The table displays coefficients α_0 and β^r from specification 4. The regression consists of four categories: other investors, most underfunded, medium underfunded, and least underfunded public pension supported firms. Column (1) reproduces estimates from table 9 column (3), and column (2) uses state public union density of corresponding public pensions supporting target firms. Regression estimates are weighted by employment in buyout year t_0. Standard errors are clustered at the firm level to account for potential heterogeneity. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

5.3 Accounting for Political Motives of Pensions

A potential story might be that public pensions have political incentives which might influence the investment officer's investment decisions. However, due to the limited parnership structure of investors, the investment officers decide which private equity funds to invest in and not the target firms directly. Hence, it is unlikely differences in target firms are driven by investors' political motives.

To further rule out this concern, I conduct a robustness check where I remove investments by investors (via private equity funds) to target firms in the same state. Figure 21 shows that by limiting the sample to out of state investments in target firms relative to the investors' states, roughly gives the same estimates. Instead of the −5.20 labor productivity estimate for targets supported by the most underfunded pensions in Figure 6, I find a −4.67 in Figure 21. This implies that 89.8% of the magnitude is still prevalent.

6 Relation of cross-sectional estimates to aggregate

In this section, I revisit the literature on the average productivity effects of private equity buyouts (Davis et al. (2014), Davis et al. (2019)), with a larger sample and a longer time period covering the new capital inflow from public pensions to private equity. The goal of this section is to see how the cross-sectional estimates relate to the aggregate estimates.

6.1 Comparing PE Targets with Non PE Targets

I build on the main specification in Davis et al. (2014), by comparing outcome variables of firms bought by private equity with similar firms not under private equity influence. It would be ideal to have an exogenous shock to capital flow in private equity funds across all industries. However, since the exogenous shocks exist in specific industries, the literature has relied on granular Census data to contruct control firms to study private equity targets across industries.

The control firms consist of active entities in the buyout transaction year, which are in the same industry, firm size, firm age, and multi-unit status group (referred to as "cell") as the target firms, but are not bought by private equity during their entire history.[19] I face two challenges in this approach. First, since my control firms comprise of the universe of firms not bought out by private equity, and an entity can be a control for different targets in different years of buyout, I run into computing constraints during empirical analysis. Second, the control group exceeds the treated group. To address these concerns, I select a 10% random sample from the universe of controls for each cell. Online Appendix C.2 shows robustness to different random samples. I conduct the analysis with variables available at the Census for all industries: employment, real revenue, revenue per employee, real pay, and pay per employee at the firm level. I present the raw data in Online Appendix C.

The difference in difference specification compares the treated and control firms 5 years pre and post-buyout,

$$y_{it} = \alpha_t + \sum_{j=-5, j\neq -1}^{j=+5} \gamma_j \Big(\text{PE}_i \times \text{Buyout Year}_{it_0+j}\Big) + \sum_c \theta_c D_{cit} + \lambda_0 \text{LFIRM}_i + \varepsilon_{it} \tag{8}$$

[19] Control cells are constructed based on the cross product of the above categories. Firm size categories are 1-4, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, 1,000-2,499, 2,500-4,999, 5,000-9,999, and greater than 10,000 employees. Firm age categories are 0-5, 6-10, 11-15, 16-20, and 21 or more years. There are 22 industries defined based on two-digit NAICS codes, a dummy for multi-unit status, and the year of buyout transaction. I use NAICS code because of better coverage in Revenue Enhanced LBD.

PE_i takes the value of 1 for firms bought by private equity, and 0 for the controls. Buyout Year_{i,t_0+j} is a dummy for each j taking a value of 1 in the year $t_0 \pm j$ relative to buyout year, with $j = -5, \cdots, 5$. The coefficient of interest is γ_j which measures the effect of private equity buyouts on targets relative to control firms in each of the 5 years pre- and post-buyout. As a standard practice, the year before buyout $t_0 - 1$ is the omitted category, and years beyond 5 years pre- and post-buyout are binned with year +/-5 relative to buyout. The regression is saturated with 5,600 dummies D_{cit} capturing industry $\times$ size $\times$ age $\times$ type $\times$ buyout year ("cell"). I control for lagged firm growth from $t_0 - 3$ to $t_0 - 1$, LFIRM_i. My difference in differences design does not suffer from bias as in settings of staggered treatmeants argued in recent papers (Goodman-Bacon (2021), Sun and Abraham (2021), Athey and Imbens (2022), Borusyak, Jaravel and Spiess (2021), de Chaisemartin and D'Haultfoeuille (2019)) as my control group consists of firms never bought by private equity. I do not include firm fixed effects as my outcome variable is in growth rates. To capture the relative business significance of entities, the empirical specification is weighted by employment at the time of buyout. Standard errors are clustered at the firm level to account for potential heterogeneity.

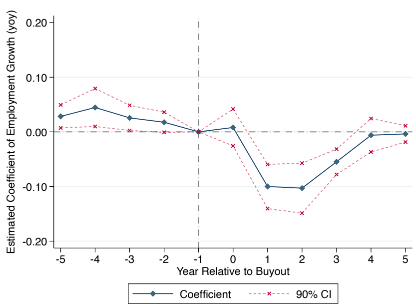
Figure 10 tracks the coefficients γ_j 5 years pre- and post-buyout. Panels A-C show year over year growth rates, and panel D shows cumulative changes. There are three main takeaways. First, employment declines 23.8%, revenue by 23.2 %, and labor productivity by 0.4% 5 years post buyout at targets relative to a control group of firms. Further, most of the employment decline happens in the first two years. Second, the parallel trends assumption of the difference in difference specification are near satisfied. With additional controls (Online Appendix), parallel trend assumptions are satisfied. This evidence suggests causal effect of private equity buyouts on target firms relative to controls, with the caveat that I am unable to completely rule out selection since I do not observe the information set of private equity fund managers.

6.1.1 Subsample Analysis

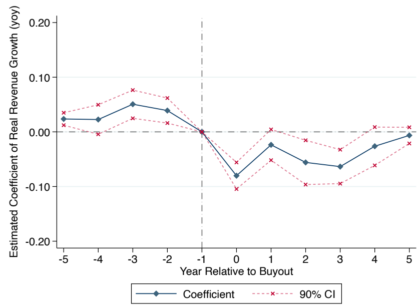
The average labor productivity effects post private equity buyouts for the period 1997 to 2018 mask considerable variation across time periods. First, I revisit the sample period in Davis et al. (2019), i.e., upto 2011 with their methodology and my sample of private equity deals.[20] When studying 3,700 private equity targets during 1999 to 2011, I find a two-year cumulative +7.3% labor productivity change for targets relative to control firms post buyout, similar to Davis et al. (2019) which finds a two-year cumulative change of +7.5% for deals

[20] I cannot verify my deal sample against theirs because of Census project rules.

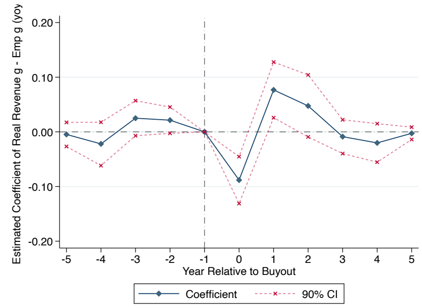
Figure 10. Difference in Difference Estimated Coefficients γ_j Over Time Relative to Buyout Year, PE Deals 1997-2018



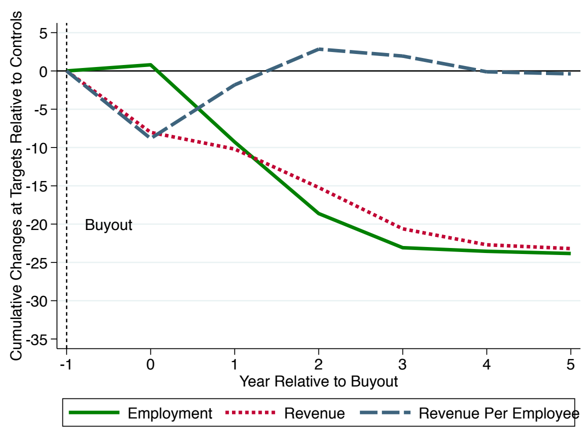
(A) Employment g



(B) Revenue g



(C) Rev g - Emp g



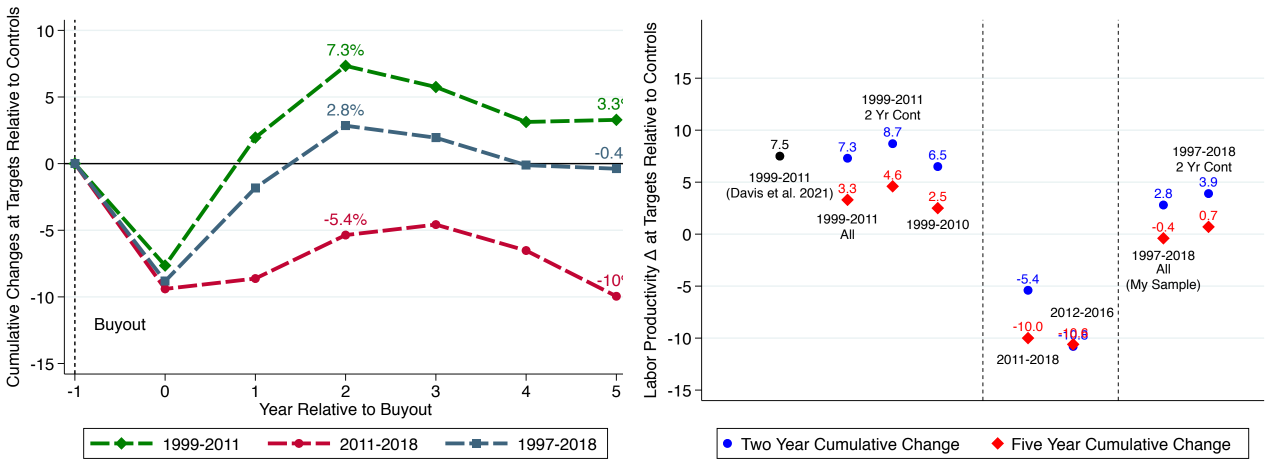
(D) Cumulative Changes

Notes: Figure plots difference in difference coefficients γ_j from equation 8 for years -5 to +5 relative to buyout for employment (panel A), revenue (panel B), and revenue minus employment (panel C) growth rates. Dotted red lines represent 90% confidence intervals. Panel D plots cumulative changes from estimates in panels A-C, normalized to 0 in year -1 relative to buyout. The private equity transaction takes place between year-1 and 0.

executed during this time period (Figure 11). When I look at the following period from 2011 to 2018 using my large sample of deals, I find a two-year cumulative labor productivity change of -5.4%. When studying the full sample of private equity deals from 1997 to 2018, I find a positive two-year labor productivity change of $+2.8\%$. Negative labor productivity changes in the second half of the sample, subdues the effects for the full sample period.

Second, I show that the five-year labor productivity changes are less than two-year changes across time perods. Longer time periods have not been studied in the earlier literature. Panel B shows the red dots are lower than blue dots. This is also true for firms which continue to exist post two years after buyout. Importantly, both two year and five year productivity changes are lower in 2011-2018 as compared to 1999-2011.

Figure 11. Labor Productivity Changes Across Sample Periods



(A) Across Periods **(B)** Comparison with Previous Literature

Notes: Panel A shows cumulative labor productivity changes post buyout considering targets from the deal period: (1) 1999-2011, (2) 2011-2018, and (3) 1997-2018. 1999-2011 is the sample period considered in Davis et al. (2019). 1997-2018 is my main sample period. The second panel shows two year and five year cumulative labor productivity changes for different time periods. The figure compares my estimates with earlier studies. "2 Yr Cont" refers to firms continuing for at least two years post buyout.

6.2 Discussion

I show that the labor productivity changes are negative in the second half of the sample period, which brings down the average for the full sample. This coincides with public pensions financing small and new private equity funds, and inturn those private equity funds financing firms which show decreases in labor productivity measures in the second half of the sample. This suggests that the most underfunded pensions matching with the small private equity funds in the later period are bringing down the average estimate.

It would have been ideal to observe the cost measures at target firms, to have a robust measurement of productivity. But since the Census micro-data provides revenue, employment, and wages for all industries, labor productivity or revenue minus pay per employee is the widely used measurement in the literature. I find that the most underfunded pensions receive low returns relative to the least underfunded pensions, and returns to pensions depends on portfolio investments of private equity funds, hence returns can be thought of capturing the costs which labor productivity misses.

7 Economic and Policy Implications

7.1 Economic Implications

In this section, I interpret the changes in employment, dollar value for revenue, and revenue per employee based on the estimates produced in previous sections. Table 7 shows the economic loss in terms of revenue per employee at target firms relative to the control firms in the aggregate. Magnitudes are based on private equity deals from 2000 to 2015 to allow firms to be tracked for a full three year period before and after the change. The table shows changes in magnitude and percentages between one year before and three years after buyout. Panel A does not include the estimation results and studies raw data. Total employment declined by 1.5 mn. jobs at target firms, which is a -25.6% change. Total revenue declined by \$670 bn. in 2020 dollars. This corresponds to revenue decreasing by \$39,850 per employee.

Public pension fund assets were \$4.1 tn. in 2021, and on average, they invested 10.8% of their assets in private equity. This corresponds to \$445 bn. In the next exercise (panel B), I use labor productivity growth rate estimates from figure 22 and their corresponding revenue and employment growth rate estimates to present back of the envelope calculations on economic changes by investor. I cumulate annual growth rates to estimate percentage changes from time period -1 to +3 relative to buyout. Employment at firms targeted by the most underfunded public pensions decreases by 26.3%, while employment at those targeted by other investors decreases jobs by 41.7%. This corresponds to a loss of $122,000$ and $450,000$ total jobs at these firms respectively.

Other investor supported firms face a lower decrease in revenue than the most underfunded pension supported firms in percentage terms, i.e., -14.0% as compared to -38.0%. Consequently, revenue per employee decreases by 16.2%, or \$54,098 for the most underfunded pension supported firms. Average revenue per employee increases by \$193,729 for the other investor firms. Average of cumulative changes of revenue per employee across categories is approximately equal to the average change overall.

7.2 Policy and Broader Implications

Pension funds are the largest players in private equity. Public pension funded ratio is assets divided by liabilities, where liabilities in each year is the present discounted value of all future obligations. There is no one defined discount rate for U.S. state pensions to value liabilities as in Europe (Greenwood and Vissing-Jorgensen (2018)). Individual plans assume a future rate of return for their assets, and use it to discount liabilities. The median pension

Table 7. Economic Loss and Gain by Investor in terms of Labor Productivity at Target Firms Between Year −1 and +3 Relative To Buyout

		Employment		Revenue		Revenue Per Employee	
		(1) (000s)	(2) (%)	(3) ($$ Bn.)	(4) (%)	(5) ($$)	(6) (%)
Panel A: Targets Vs. Controls in Raw Data							
All	Targets	−1,500	−25.6	−670	−34.6	−39,850	−12.0
	Controls		+0.3		+2.6		+2.3
Panel B: Using Estimates from Event Study							
Targets	Most Underfunded	−122	−26.3	−59	−38.0	−54,098	−16.2
	Medium Underfunded	−199	−21.5	−61	−23.7	−1,104	−3.9
	Least Underfunded	−386	−15.0	−149	−19.5	−17,450	−5.9
	Other Investors	−450	−41.7	−77	−14.0	193,729	+38.0

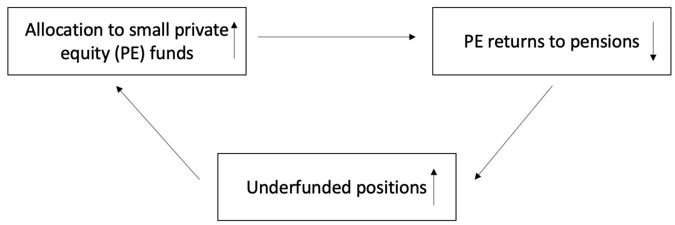
Notes: The table presents changes in employment (columns (1)-(2)), revenue (columns (3)-(4)), and revenue per employee (columns (5)-(6)) from one year pre to three years post buyout. PE deals from 2000-2015 are considered to allow firms to be tracked for a full three year period before and after the change. Panel A shows changes for targets and controls in magnitude and percentages using the raw data. Magnitude changes for controls is omitted due to large sample size differences in control and treated firms. Panel B shows changes using estimates from dynamic version of the event study 4. Revenue is deflated by the U.S. GDP Price Deflator Series, and is expressed in 2020 U.S. dollars.

plan return was 8.0% in 2007, and decreased to 7.3% in 2017.

An increase in assumed returns, mechanically decreases present value of liabilities, and increases funded ratios. This obscures the true extent of public pension liabilities, and furthers their incentives towards high return assets, like private equity. However, my paper shows that ex-post more underfunded public pensions invest in smaller private equity funds which gives them lower returns. This supports the discussion of valuing liabilities, which are hard obligations to pay retirees, using the risk free rate (Novy-Marx and Rauh (2011)). Not only are public pensions understating their costs to pay public sector employees, but their investment allocations also go to projects funded my small private equity funds which suffer on the labor productivity measures.

U.S. public pensions had $4.1 tn. assets in 2021, and supported 14.7 mn. active members and 11.2 mn. retirees. Public pension plans generally rely on the state coffers if pension obligations are not met. Hence, underfunded positions of public pensions also have broader implications for municipal and state finances, and potential stability of retirement systems. Investment returns are one of the major sources of financing for public pensions. Understanding of pension funds' investment allocation decisions and incentives in private markets, which are opaque and transaction based is key for policy making. As more underfunded pensions are matching with smaller private equity funds and receiving lower total returns. This will further decrease their underfunded pensions for following years, giving them a higher incentive to swing for high returns, pushing them into an "underfunding loop".

Figure 12. Schematic Depiction of an Underfunding Loop



The phenomenon of desperate capital and ending up with worse returns, applies to a number of situations across asset classes. For instance, my study helps us infer more broadly about the quality of transactions and investor-type matches in other assets in private markets, such as real estate, private debt, venture capital, which are equally difficult to value. One can also expand this notion to focus on other investors beyond private assets.

8 Conclusion and Future Research

This paper studies investment allocations of U.S. public pensions in private equity, based on their degree of underfunded positions. I trace their investments to the ultimate micro assets – the portfolio companies which the private equity funds invest in.

First, I show that U.S. public pensions have increased their allocations to alternative assets post the financial crisis. Even within the public pensions, it is the most underfunded public pensions which have emerged as a dominant investor in private equity. Underfunded positions of pensions have increased post the financial crisis and have remained elevated, while at the same time new private equity capital increased. Motivated by these facts, I show that the most underfunded public pensions match with the smallest private equity funds, and realize lower total returns from private equity.

Second, I study the target investments of private equity funds financed by underfunded public pensions to track the capital. Since most of these firms are private, I compile a novel dataset of public pension and private equity fund (within a fund family) linkages, along with the target firms merged with the Census micro-data, to track the full chain of capital flow from end investor to end recipient. I show that firms with the most underfunded public pensions as the dominant investor, experience a -5.2% labor productivity change per year post buyout, whereas firms majorly financed by investors other than public pension funds experience a +5.2% productivity gain. Further, targets financed by small private equity funds show decreases in productivity. This confirms the matching story in the first part. I show evidence for public pensions gambling for ressurection. To strengthen causality from underfunded positions, I use a novel instrument of variation in public unionization rates across state-year, and confirm the matching between public pensions and private equity funds due to their underfunded positions.

Lastly, I revisit the literature of average effects of private equity buyouts to connect the cross-sectional results from the earlier parts to the aggregate. I show that target firms do not experience increases in labor productivity from 1997 to 2018. The negative estimates from the second half of the sample, when the presence of public pensions in private equity increased, can be one of the reasons pulling down the average for the whole sample period and speaking to the debate of decreasing returns to private equity over time. This study has important policy implications for potential stability of retirement systems, exposing pensions to an "underfunding loop" with the current liability discounting strategy.

When studying the micro investments of pensions – the private equity targets – the literature has looked at labor productivity as the Census micro-data makes employment and revenue measures available to researchers. It would be very insightful for future research to push on accurate cost measurement or imputation. This paper does not address if the gambling for resurrection strategy is optimal for pensions. If the pensions get a very big lottery, it might be optimal but if they get small wins and large losses, it might not be. Private equity are long term investments and will need to be observed for a longer time.

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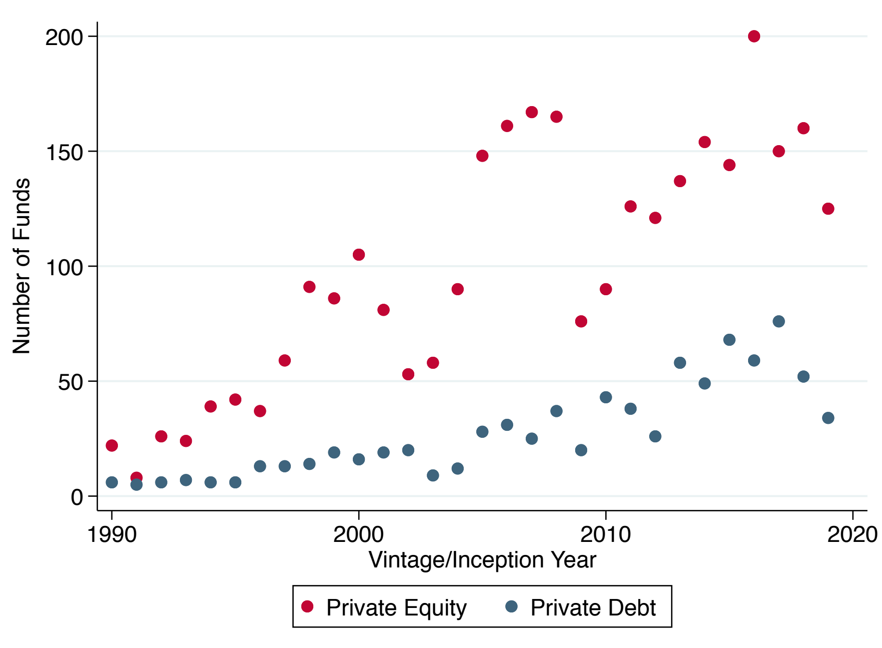
A Additional Figures and Tables

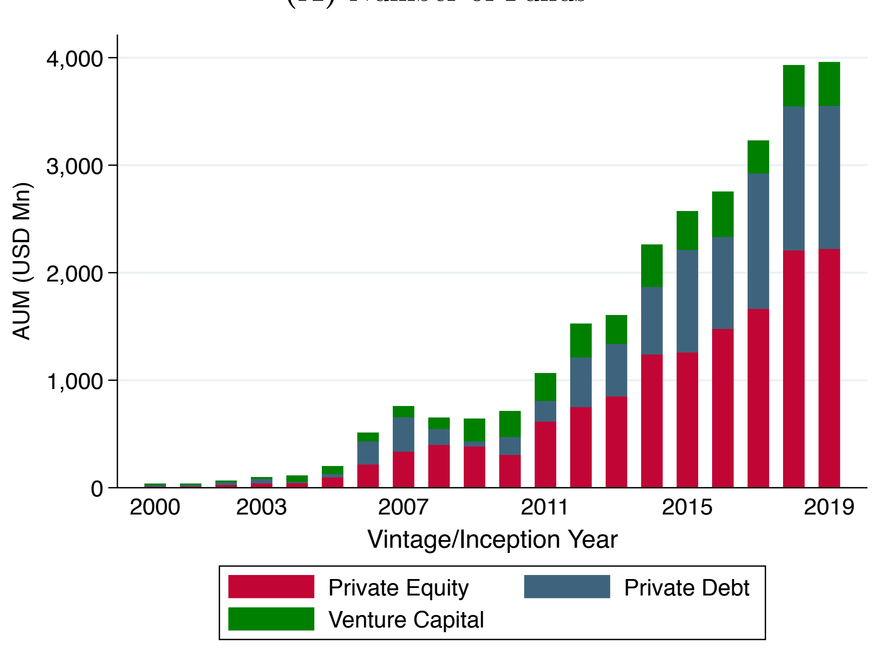
Figure 13. Funded Positions of U.S. Public Pension Funds

Notes: Funded positions are calculated as assets divided by liabilities. Liabilities in a year is the present discounted value of liabilities in the future. Source: Public Pensions Database.

Figure 14. Number of PE and PD Funds Over Years



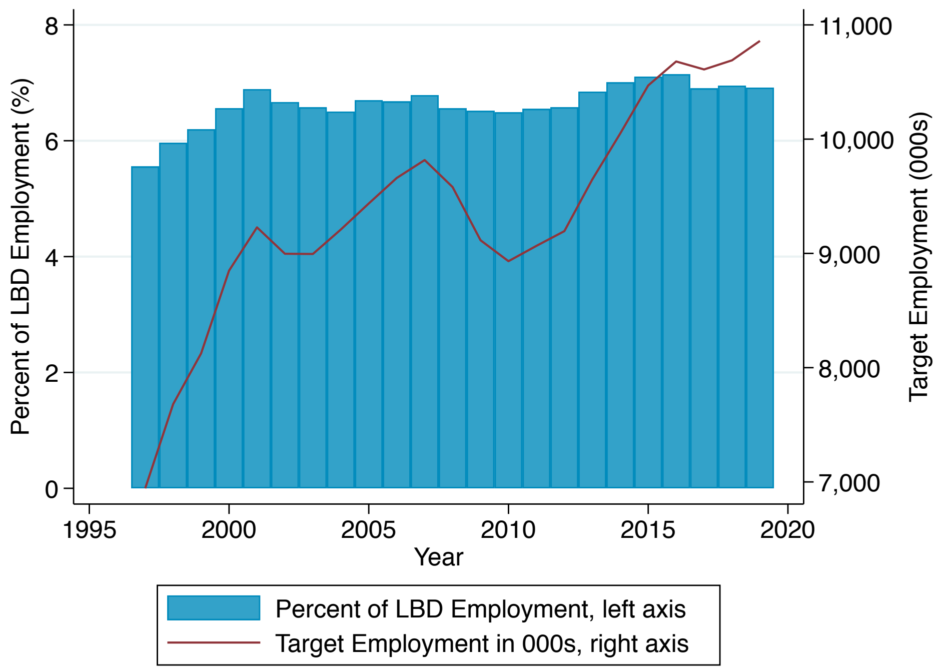
(A) Number of Funds



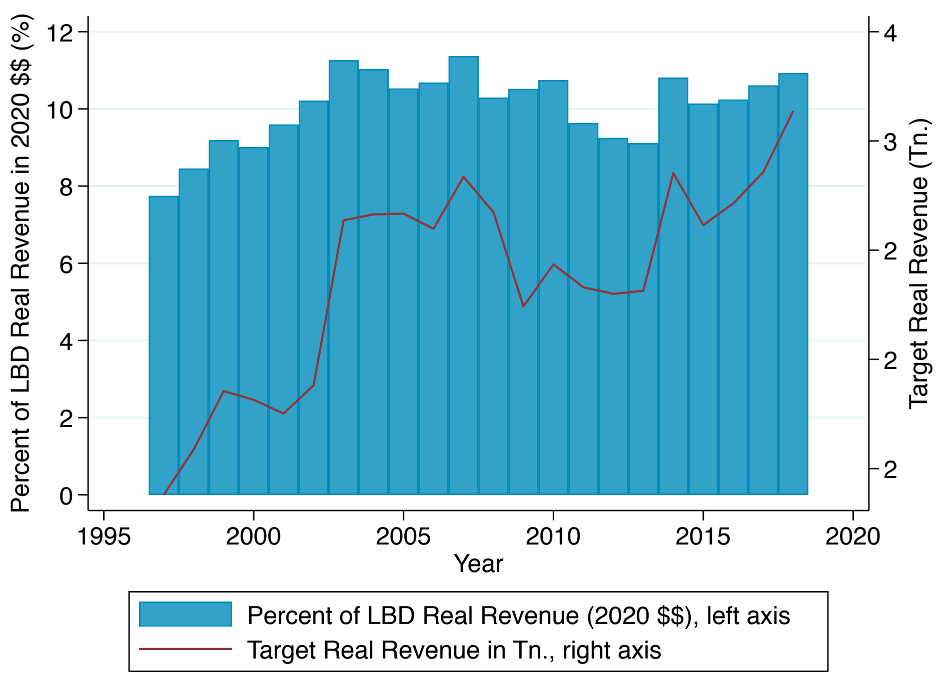
(B) AUM by Fund Type

Notes: Vintage/Inception Year is the year the fund is set up in. Data are sourced from Preqin.

Figure 15. U.S. PE Target Employment and Revenue as a Percentage of Total Non-Farm Payroll Employment and Revenue Over Time



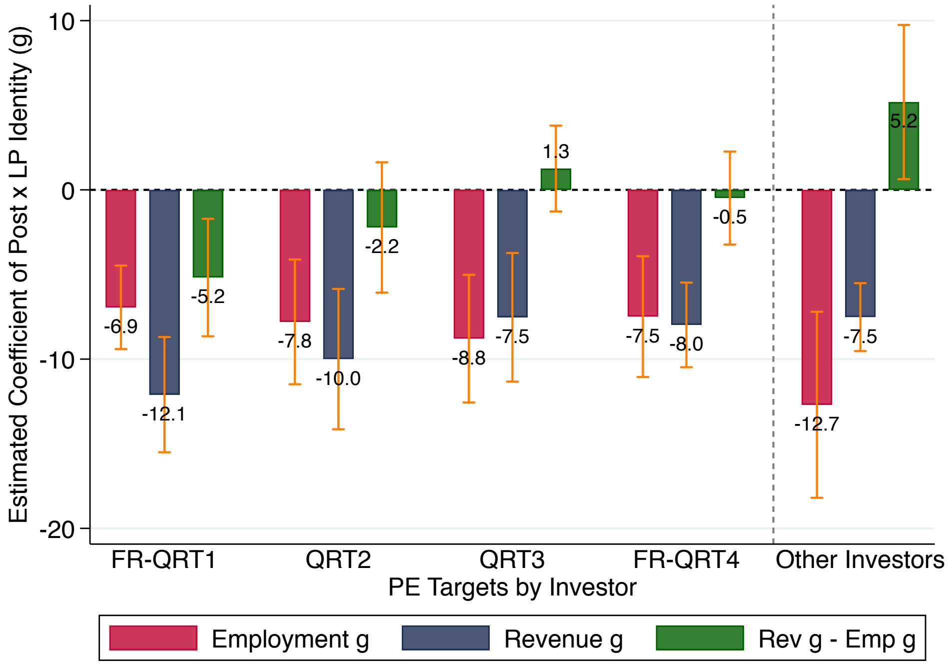
(A) Employment



(B) Revenue

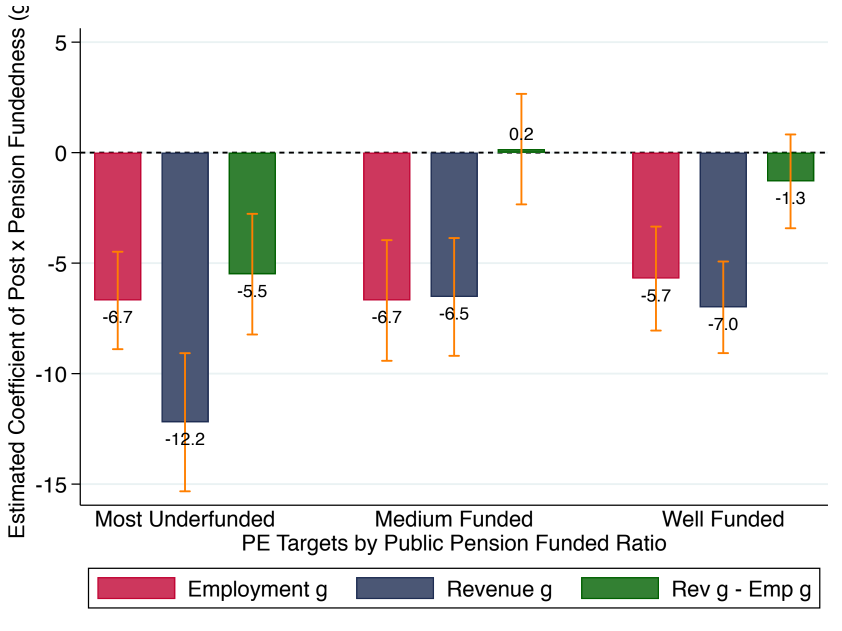
Notes: The above figures plot employment and revenue of U.S. PE Targets matched with Census micro-data. The blue bars represent employment (revenue) in PE targets as a percent of total LBD employment (revenue) over time on the left axis. The red line shows total employment (revenue) in raw numbers for matched PE targets on the right axis. Revenue is in real 2020 dollars.

Figure 16. Estimates of Post Buyout × Investor Type, Private Equity Deals 1997-2018

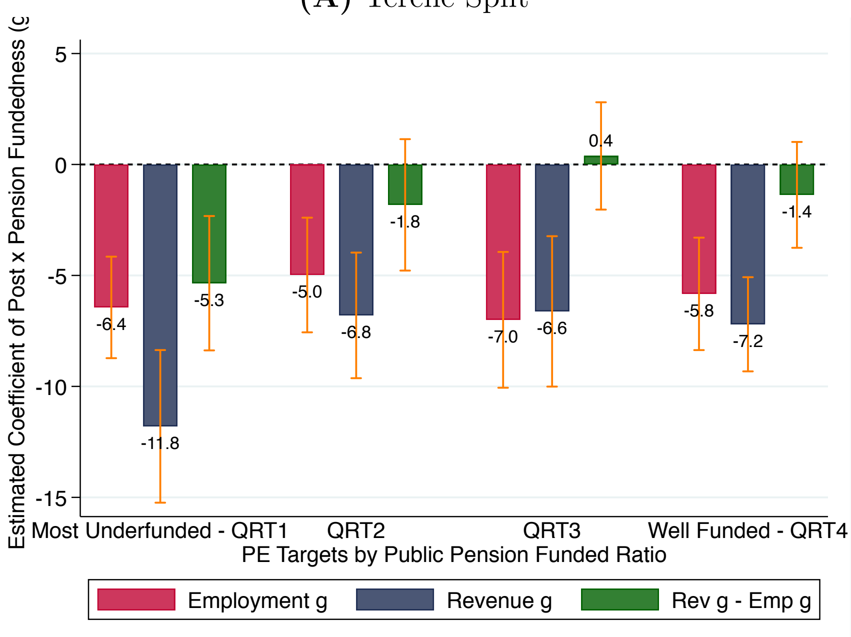


Notes: The figure plots estimated coefficients from equation 4 for employment (red), revenue (blue), and labor productivity (green) growth rates. Public pension supported firms are split into quartiles. Standard errors are clustered at the firm level. Orange lines represent 90% confidence intervals.

Figure 17. Estimates of Post Buyout × Underfunded Ratio, Private Equity Deals 1997-2018



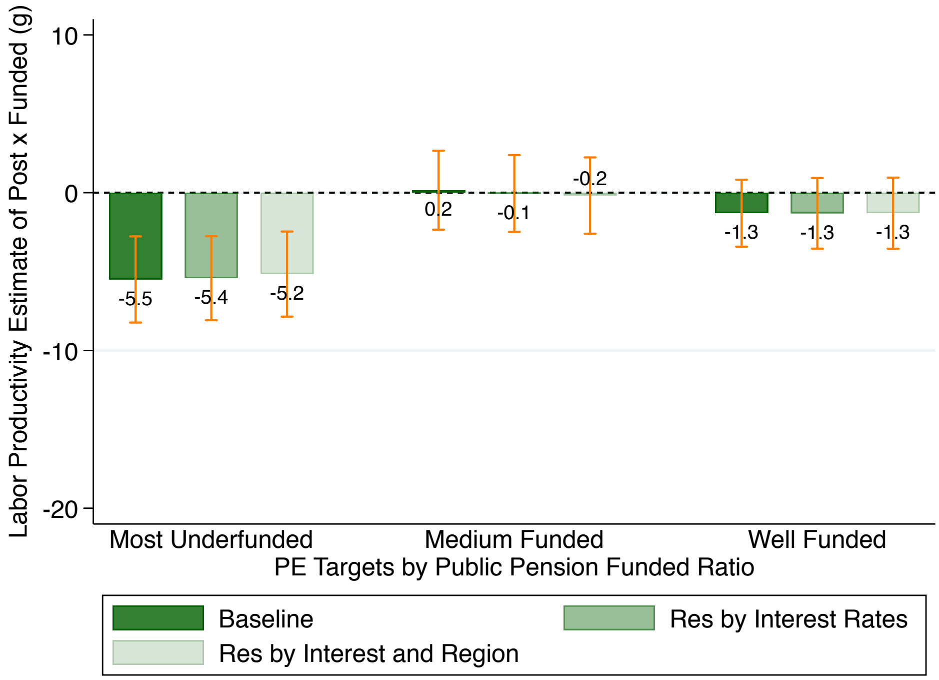
(A) Tercile Split



(B) Quartile split

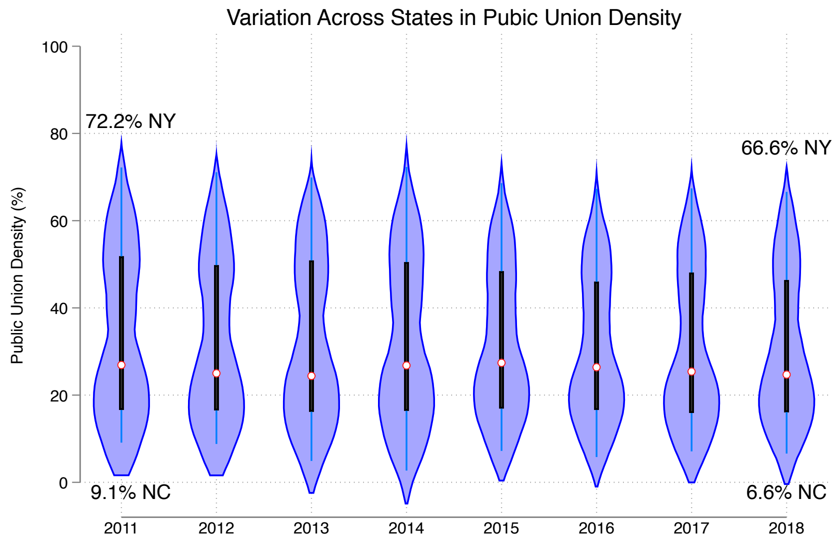
Notes: The above figures plot estimated coefficients for employment (red), revenue (blue), and labor productivity (green) growth rates of Post × Pension Underfunded Split in equation 4 for each tercile (panel A) and quartile (panel B) of firms. Firms are split based on the weighted average of underfunded positions of public pensions supporting the firms. Weights are capital commitments by each pension in the firm via PE funds. Orange lines represent 90% confidence intervals.

Figure 18. Labor Productivity Estimates of Post Buyout × Underfunded Ratio, Residualized for Macroeconomic Conditions, Private Equity Deals 1997-2018



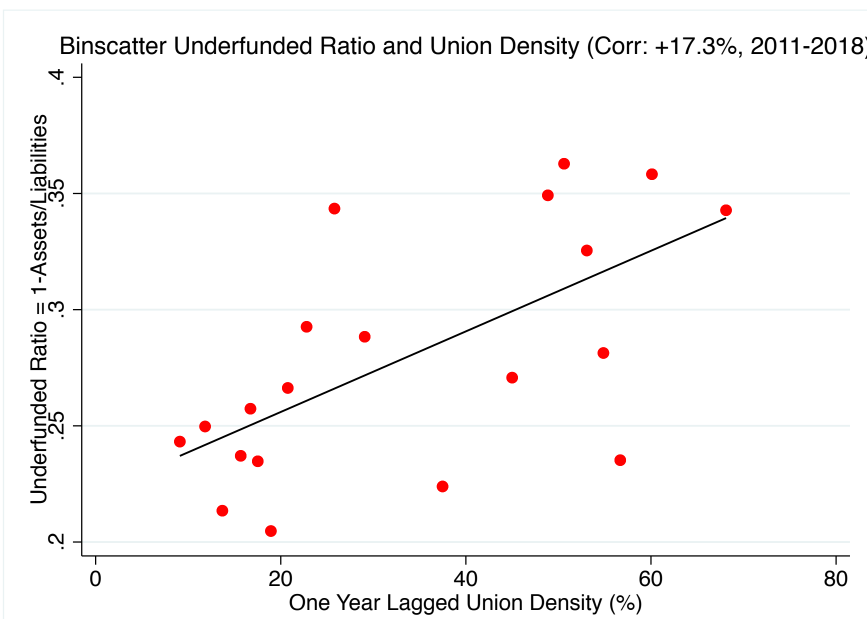
Notes: The figure plots estimated coefficients for labor productivity growth rates of Post × Pension Underfunded Split in equation 4 for each tercile of firms. Different shades of bars correspond to underfunded ratios of pensions post *residualizing* for different macroeconomic conditions. Firms are split based on the weighted average of underfunded positions of public pensions supporting the firms. Weights are capital commitments by each pension in the firm via PE funds. Orange lines represent 90% confidence intervals.

Figure 19. Variation in Public Union Density Across States, 2011-2018



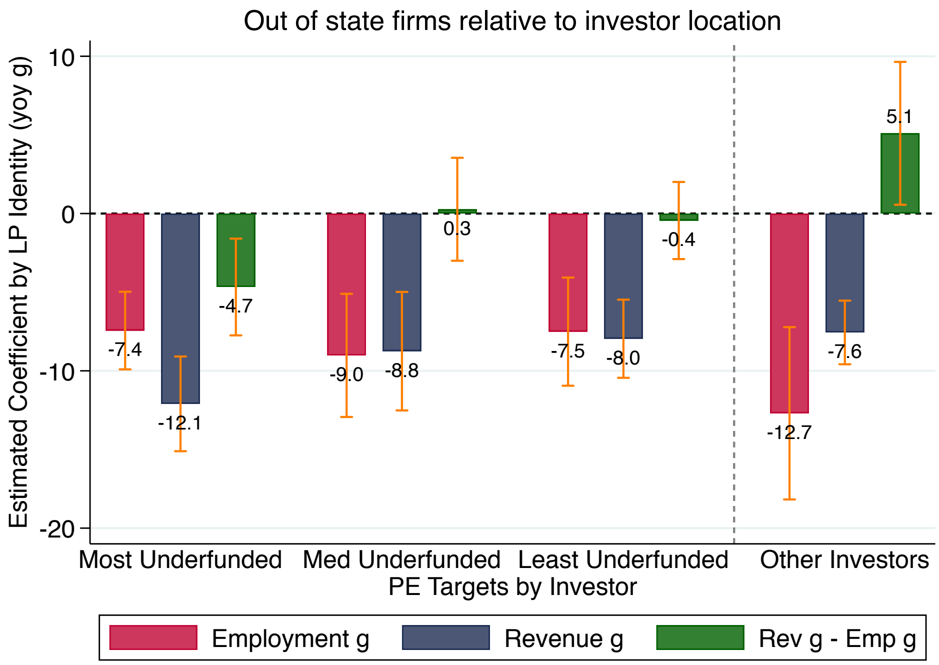
Notes: Figure shows variation in public union density across states over time. Public union density is defined as the percentage of public workers which are part of a union. Dispersion is similar for years not reported. Data are sourced from CPS and Union Stats.

Figure 20. Correlation Between Underfunded Ratio and One Year Lag Public Union Density



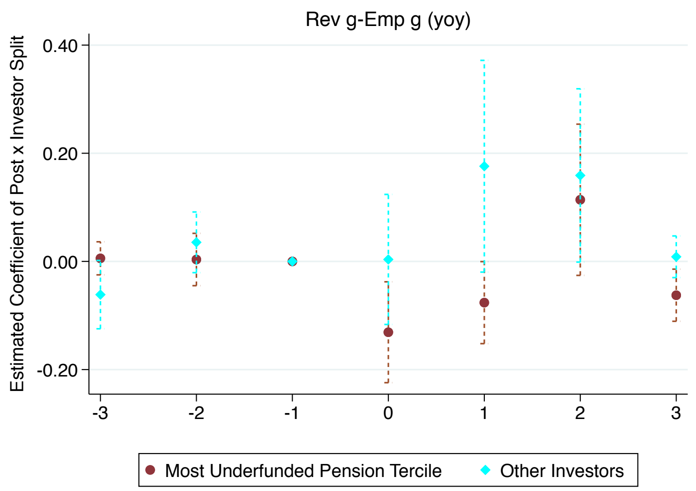
Notes: Figure plots a binscatter of underfunded ratio against one year lag of union density amongst public workers. Public union density is defined as the percentage of public workers which are part of a union. Underfunded ratio is one minus assets divided by liabilities for public pension plans. Figure uses the time period 2011-2018, correlation is positive +17.3% and significant. For the time period 1997-2018, correlation is positive +6.3% and significant. Balance sheet fundamentals of public pensions are sourced from Public Pensions Database and FOIA requests. Union density is sourced from CPS and Union Stats.

Figure 21. Labor Productivity Estimates of Post Buyout × Underfunded Ratio, **Out of State Investments**, Private Equity Deals 1997-2018



Notes: The figure plots estimated coefficients for labor productivity growth rates of Post × Investor Type in equation 4 for four categories: other investors, most underfunded, medium underfunded, and least underfunded public pension supported firms. I remove investors' investments in target firms (via private equity funds) for firms which are in the same state as the investor. Firms are split based on the weighted average of underfunded positions of public pensions supporting the firms. Weights are capital commitments by each pension in the firm via private equity funds. These are total coefficient estimates, bars represent 90% confidence intervals.

Figure 22. Labor Productivity g Dynamic Estimates for Post Buyout $\times$ Investor Type Over Time Relative to Buyout Year, PE Deals 1997-2018



Notes: Figure plots coefficients β_j^r, $j = -3, \cdots, 3$ for the dynamic version of equation 4 for three years before and after buyout for the most underfunded and other investor category of firms. Connected lines represent 90% confidence intervals.

Table 8. Estimated Coefficients for Post Buyout by Investor Identity, PE Deals 1997-2018

Dependent Variable:	Emp g (1)	Rev g (2)	Rev g-Emp g (3)
	Panel A: Investor Identity Split		
Post Buyout (Base: Other Investors)	-0.1280^{***}	-0.0760^{***}	0.0516^{*}
	(0.0325)	(0.0119)	(0.0275)
Post Buyout $\times$ Public Pensions	0.0490^{*}	-0.0091	-0.0580^{**}
	(0.0278)	(0.0112)	(0.0250)
Observations	56,000	56,000	56,000
Adjusted R^2	0.1910	0.1370	0.0191
Dependent Variable Mean	0.0232	0.0252	0.0020
	Panel B: All		
Post Buyout	-0.0884^{***}	-0.0833^{***}	0.0052
	(0.0181)	(0.0119)	(0.0136)
Observations	56,000	56,000	56,000
Adjusted R^2	0.1890	0.1370	0.0166
Dependent Variable Mean	0.0232	0.0252	0.0020
Year FE	Y	Y	Y
Firm Size FE	Y	Y	Y
Firm Age FE	Y	Y	Y
Industry FE	Y	Y	Y
Type of Unit FE	Y	Y	Y
Lagged Firm g	Y	Y	Y
Weighted Emp t_0	Y	Y	Y

Notes: The table displays coefficients α_0 and β^r from specification 4. The regression consists of two categories: other investors and public pension supported firms. Regression estimates are weighted by employment in buyout year t. Standard errors are clustered at the firm level to account for potential heterogeneity. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 9. Estimated Coefficients for Post Buyout by Investor Type and Public Pension Fund Ratio, PE Deals 1997-2018

Dependent Variable:	Emp g (1)	Rev g (2)	Rev g-Emp g (3)
	Panel A: Investor Split		
Post Buyout (Base: Other Investors)	-0.1270^{***}	-0.0748^{***}	0.0522^{*}
	(0.0333)	(0.0122)	(0.0276)
Post Buyout × Most Underfunded Pensions	0.0526^{*}	-0.0517^{***}	-0.1040^{***}
	(0.0312)	(0.0198)	(0.0301)
Post Buyout × Medium Underfunded Pensions	0.0334	−0.0132	−0.0466
	(0.0319)	(0.0218)	(0.0295)
Post Buyout × Least Underfunded Pensions	0.0528^{*}	−0.0032	-0.0559^{**}
	(0.0284)	(0.0121)	(0.0260)
Observations	53,500	53,500	53,500
Adjusted R^2	0.1920	0.1450	0.0203
Dependent Variable Mean	0.0249	0.0252	0.0003
	Panel B: All		
Post Buyout	-0.0874^{***}	-0.0845^{***}	0.0029
	(0.0196)	(0.0125)	(0.0148)
Observations	53,500	53,500	53,500
Adjusted R^2	0.1900	0.1440	0.0165
Dependent Variable Mean	0.0249	0.0252	0.0003
Year FE	Y	Y	Y
Firm Size FE	Y	Y	Y
Firm Age FE	Y	Y	Y
Industry FE	Y	Y	Y
Type of Unit FE	Y	Y	Y
Lagged Firm g	Y	Y	Y
Weighted Emp t_0	Y	Y	Y

Notes: The table displays coefficients α_0 and β^r from specification 4. The regression consists of four categories: other investors, most underfunded, medium underfunded, and least underfunded public pension supported firms. Regression estimates are weighted by employment in buyout year t. Standard errors are clustered at the firm level to account for potential heterogeneity. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 10. Estimated Coefficients for Post Buyout by Pension Fund Underfunded Ratio, PE Deals 1997-2018

Dependent Variable:	Emp g (1)	Rev g (2)	Rev g-Emp g (3)
	Panel A: Pension Funded Ratio Split		
Post Buyout (Base: Least Underfunded)	-0.0570^{***}	-0.0700^{***}	-0.0130
	(0.0143)	(0.0126)	(0.0129)
Post Buyout × Most Underfunded	-0.0099	-0.0519^{***}	-0.0420^{**}
	(0.0140)	(0.0200)	(0.0188)
Post Buyout × Medium Underfunded	-0.0099	0.0047	0.0146
	(0.0159)	(0.0161)	(0.0156)
Observations	44,500	44,500	44,500
Adjusted R^2	0.2020	0.1460	0.0197
Dependent Variable Mean	0.0237	0.0223	-0.0014
	Panel B: All		
Post Buyout	-0.0601^{***}	-0.0772^{***}	-0.0171
	(0.0125)	(0.0117)	(0.0116)
Observations	44,500	44,500	44,500
Adjusted R^2	0.2020	0.1440	0.0185
Dependent Variable Mean	0.0237	0.0223	-0.0014
Year FE	Y	Y	Y
Firm Size FE	Y	Y	Y
Firm Age FE	Y	Y	Y
Industry FE	Y	Y	Y
Type of Unit FE	Y	Y	Y
Lagged Firm g	Y	Y	Y
Weighted Emp t_0	Y	Y	Y

Notes: The table displays coefficients α_0 and β^r from specification 4. The regression consists of three categories: most underfunded, medium underfunded, and least underfunded public pension supported firms. Regression estimates are weighted by employment in buyout year t. Standard errors are clustered at the firm level to account for potential heterogeneity. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Online Appendix for Desperate Capital Breeds Productivity Loss: Evidence from Public Pension Investments in Private Equity

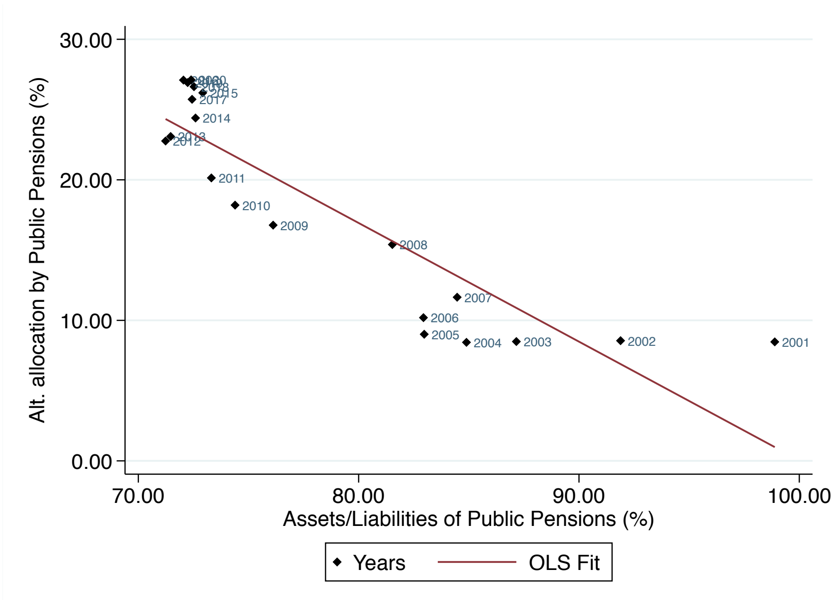
Vrinda Mittal

UNC Kenan-Flagler Business School

A Additional Results by Investors

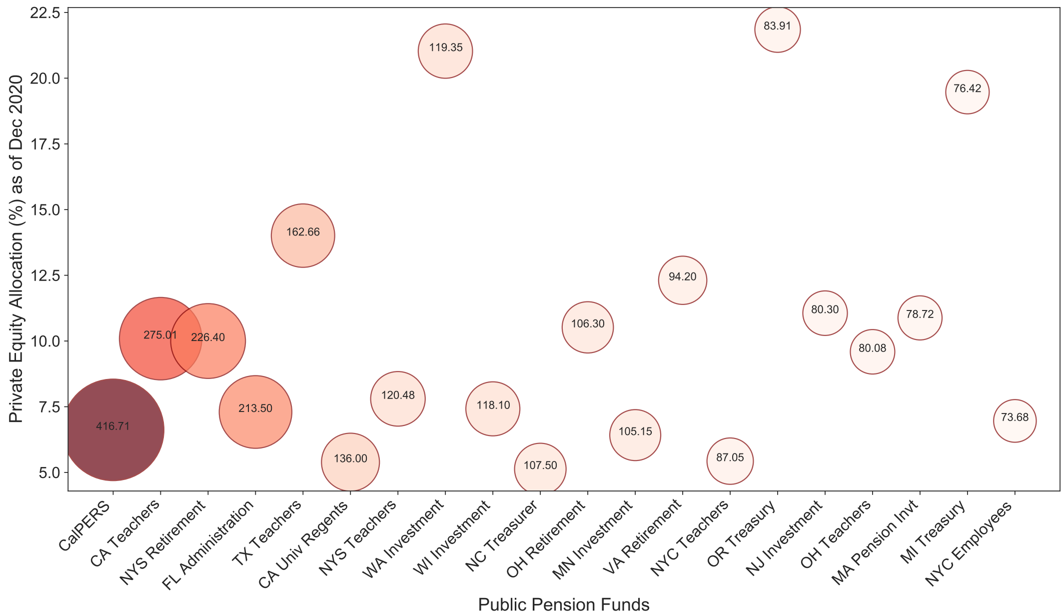
A.1 Supplemental Pension Allocation Figures

Figure A.23. Portfolio Allocations and Funded Positions of Public Pensions Over Years

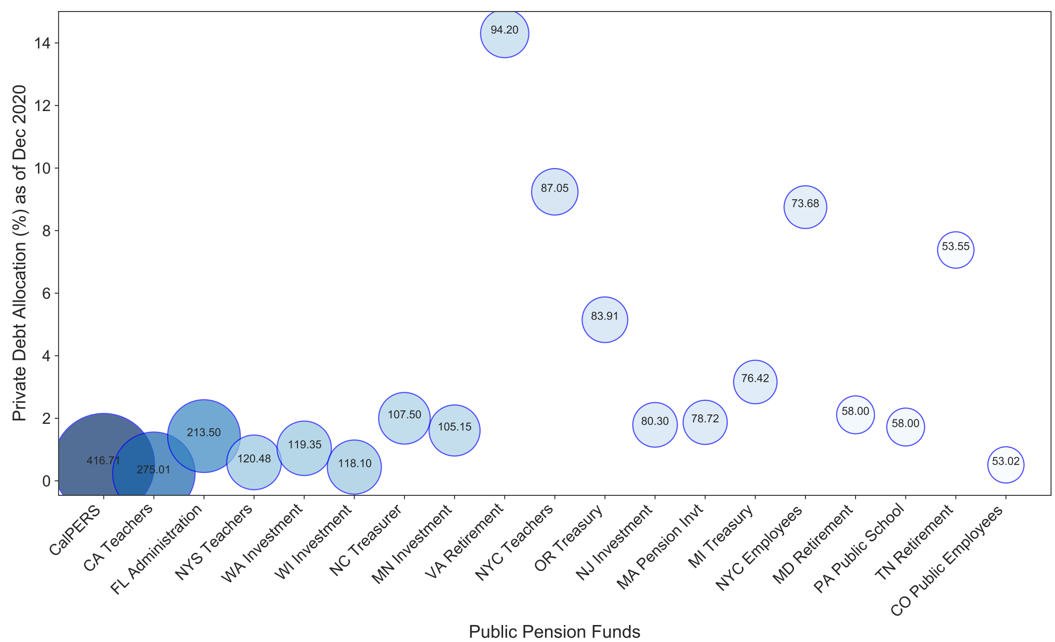


Notes: Portfolio allocations and funded positions of public pensions are sourced from Public Pensions Database, and interest rates from FRED.

Figure A.24. Private Equity and Private Debt Allocations for U.S. Public Pension Funds with AUM above $50 mn as of December 2020



(A) Private Equity



(B) Private Debt

Notes: Allocations of public pension funds with assets under management (AUM) above $50 mn. towards private equity (panel A) and private debt (panel B) as of December 2019. Size of the bubble corresponds to the size of the pension fund. Data are sourced from Preqin.

Table A.11. Private Equity and Private Debt Allocations for U.S. Public Pension Funds with AUM above $50 mn as of December 2020

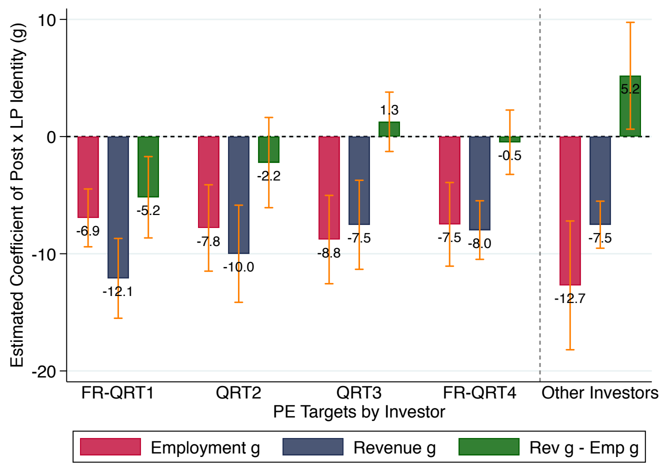
Pension Fund	AUM (USD Bn.)	PE Target Allocation (USD Bn.)	PE Allocation (USD Bn.)	PE Allocation (%)	PD Target Allocation (USD Bn.)	PD Allocation (USD Bn.)	PD Allocation (%)
CalPERS - California Public Employees' Retirement System	403.00	33.34	27.59	6.62		2.14	0.53
California State Teachers' Retirement System (CalSTRS)	275.01	25.79	26.02	10.09		0.66	0.24
New York State Common Retirement Fund	226.40	22.64	22.64	10.00			
Florida State Board of Administration	213.50	12.47	15.17	7.30	8.54	3.05	1.43
Teacher Retirement System of Texas	162.66	21.73	21.75	14.01			
Regents of the University of California	118.80	8.91	6.40	5.39			
New York State Teachers' Retirement System	118.76	9.64	9.40	7.80	1.19	0.70	0.59
Washington State Investment Board	116.98	27.45	25.10	21.03		1.22	1.04
State of Wisconsin Investment Board	116.30	12.99	8.76	7.42		0.51	0.44
North Carolina Department of State Treasurer	107.50	6.44	5.51	5.13	1.94	2.15	2.00
Ohio Public Employees' Retirement System	106.30	11.15	10.74	10.52			
Minnesota State Board of Investment	105.15		6.57	6.42		1.69	1.61
Virginia Retirement System	94.00	12.25	11.60	12.31	14.10	13.44	14.30
Teachers' Retirement System of the City of New York	87.05	4.70	4.72	5.43		8.04	9.24
Oregon State Treasury	83.91	14.69	18.34	21.85		4.32	5.15
NJ Division of Investment	80.20	10.44	8.88	11.06	6.42	1.44	1.79
State Teachers' Retirement System of Ohio	78.72	5.61	7.68	9.59			
Massachusetts Pension Reserves Investment Management Board	78.72	9.60	8.16	10.88	3.15	1.47	1.87
Michigan Department of Treasury	76.42	13.99	14.06	19.47		2.41	3.16
New York City Employees' Retirement System	72.61	5.89	5.13	6.96		6.35	8.75
Los Angeles County Employees' Retirement Association	60.73	6.07	6.98	11.49	1.82		
Pennsylvania Public School Employees' Retirement System	58.00	8.70	9.19	15.84		1.00	1.72
Maryland State Retirement and Pension System	58.00	7.54	8.24	14.20		1.22	2.11
Teachers' Retirement System of the State of Illinois	55.72	8.04	6.14	11.46	3.34		
Tennessee Consolidated Retirement System	53.55	4.82	3.98	7.44	3.75	3.95	7.38
Colorado Public Employees' Retirement Association	53.02	4.30	3.79	7.50		0.27	0.51

Notes: This table shows target and actual portfolio allocations of individual U.S. public pension funds to private equity and private debt. Public pension plans with assets above $50 bn. as of December 2020 are reported. Data are sourced from Preqin.

A.2 Additional Splits

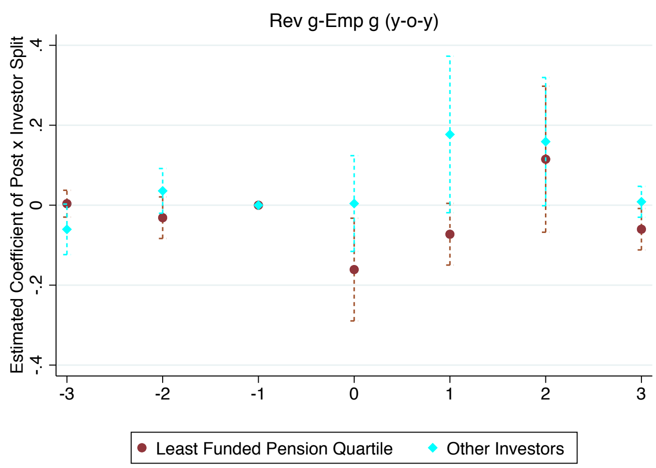
In specification 4, I split the data in terciles of different underfunded ratios. In this section, I confirm the result using quartile splits and find similar patterns. Figure A.25 shows that the most underfunded public pensions supporting significant decreases in labor productivity is not driven by chioce of splits.

Figure A.25. Estimates of Post Buyout × Investor Type, PE Deals 1997-2018



Notes: The figure plots estimated coefficients from equation 4 for employment (red), revenue (blue), and labor productivity (green) growth rates. Public pension supported firms are split into quartiles. Standard errors are clustered at the firm level. Orange lines represent 90% confidence intervals.

Figure A.26. Dynamic Estimates of Post Buyout × Investor Type Over Time Relative to Buyout Year, PE Deals 1997-2018

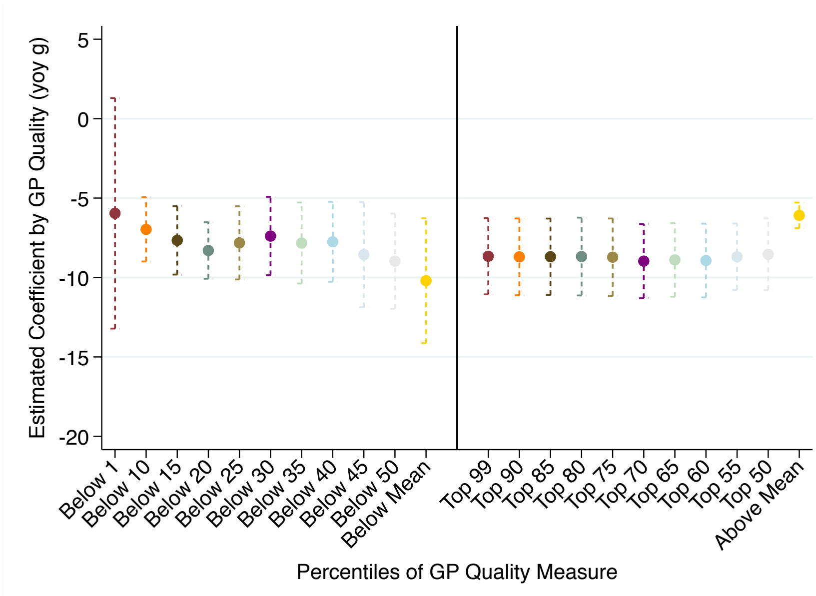


Notes: The figure plots dynamic version of estimated coefficients from equation 4 for labor productivity growth rates. Public pension supported firms are split into quartiles. Most underfunded public pension quartile is in blue, and other investors is in red. Standard errors are clustered at the firm level. Lines represent 90% confidence intervals.

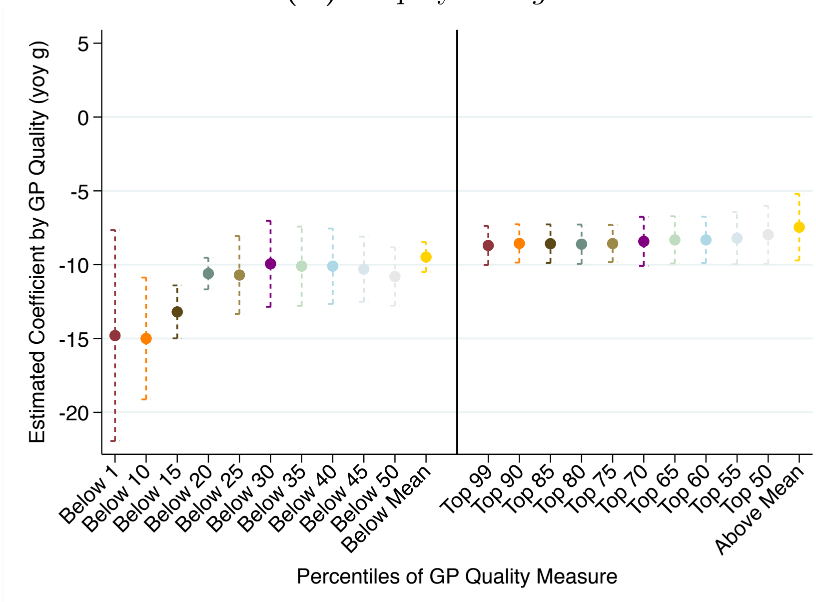
B Additional Results by Private Equity Funds

B.1 Supplemental Figures

Figure B.27. Estimates of Post Buyout × GP Quality Percentile, PE Deals 1997-2018



(A) Employment g



(B) Revenue g

Notes: The figure shows estimates from equation **??**, where GP_j is substituted with different percentile based splits of targets. Interaction term of $\left(\text{Post Buyout} \times \mathrm{LP}_k\right)$ is omitted. Each color shows estimates from one regression. Panel A corresponds to employment growth rates, and panel B for revenue growth rates. Bars represent 90% confidence intervals.

B.2 Book Value Measure of GP Quality

I construct the book value measure of skill in private equity using the total capital raised by the fund. Assets of a fund family in PE is the sum of assets of its component funds existing in that year.

$$\text{Assets}_{\mathcal{J},t} = \sum_{j \in \mathcal{J}} \text{Assets}_{j,t} \tag{9}$$

In a couple of instances, I observe the lifespan of the fund. The lifespan is the duration including first 1-2 years of capital commitments, next 5-6 years of investment, followed by 1-2 years of liquidation. The median lifespan of the funds in my sample is 10 years, similar as suggested in Kaplan and Strömberg (2009). I consider the median when the fund lifespan is not available. If the time period of the fund is given in half years, I round up to the next year. To measure the accurate significance of a fund family in the PE industry, I consider all PE funds including the ones not involved in my sample of matched deals. It is seen that the ranking of GPs based on the market value size measure and the book value size measure is consistent.

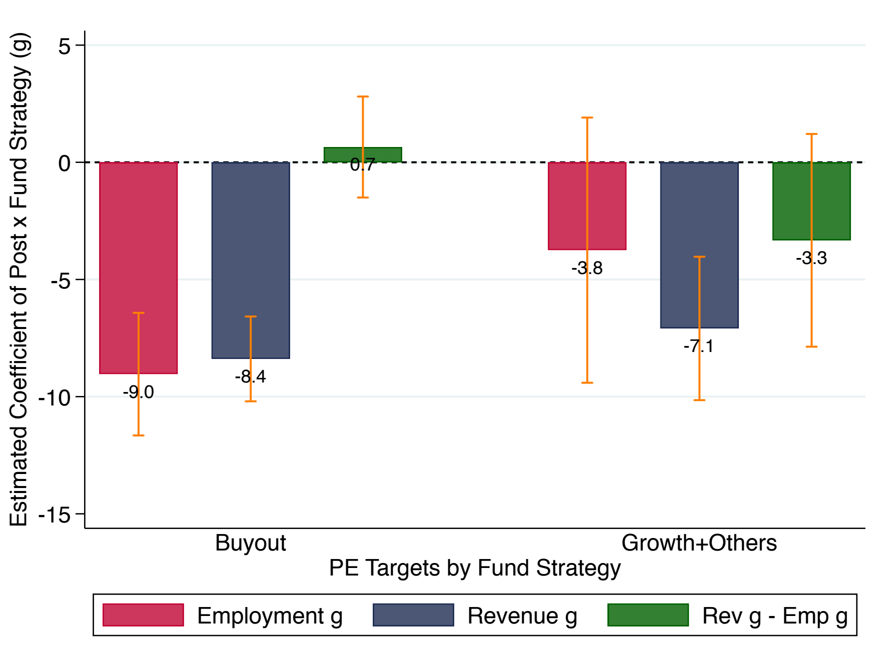
B.3 Additional Results on GP Heterogeneity

Fund Strategy

Different funds within a family can vary by strategy. In my sample, most of the funds are regular buyout funds, and a small percentage are growth firms, fund of funds, turnaround, multi-strategy etc. To study differences on targets based on fund strategy, I define a target as supported by a "growth+others" if at least one of the funds is a growth fund. The rest are classified as "buyout".

Figure B.28 shows employment, revenue, and labor productivity year over year growth rates post buyout for firms supported by buyout PE funds and growth PE funds. Growth funds supported firms experience an insignificant decrease in labor productivity by 3.3% points post buyout.

Figure B.28. Estimated Coefficients of Post Buyout × GP Fund Strategy Relative to Pre-Buyout, PE Deals from 1997-2018



Notes: The figure plots estimated coefficients for employment (red), revenue (blue), and labor productivity (green) growth rates of the Post × Fund Strategy version of equation 4. Buyout includes firms financed by only balanced buyout strategy funds. Growth+Others includes includes firms financed by at least one of growth, multi-strategy, and other funds. Standard errors are clustered at the firm level. Orange lines show 90% confidence intervals.

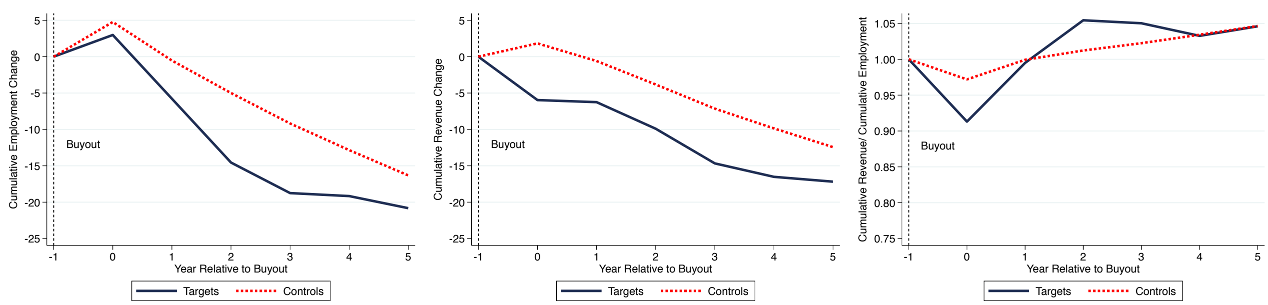
C Additional Aggregate Results

C.1 Non-Parametric Comparison

Here, I present a non-parametric comparison of cumulative growth rates in target firms minus control firms five years before and after the private equity transaction for deals from 1997 to 2018.

Figure C.29 shows that cumulating year over year employment and revenue changes, post 5 years of buyout employment decreases by 20.8% at controls and 16.3% at targets, revenue decreases by 17.8% at targets and 12.4% at controls. Combining these, revenue per employee does not change significantly between targets (+3.0%) and controls (+4.1%). Figure C.30 shows year over year growth rates. It is seen that firms in the control group also shrink post buyout but less than controls. This is not surprising as the control group is constructed on a granular matched sample approach. The industries and types of firms targeted by PE are those which require substantial restructuring.[21]

Figure C.29. Non Parametric: Cumulative Changes in Employment, Revenue, and Labor Productivity at U.S. Target and Control Firms Post Buyout, PE Deals 1997-2018



(A) Cumulative Employment Change

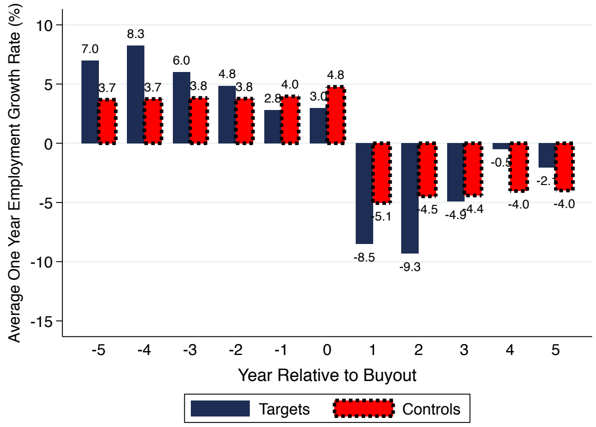
(B) Cumulative Revenue Change

(C) Cum Revenue/ Cum Employment

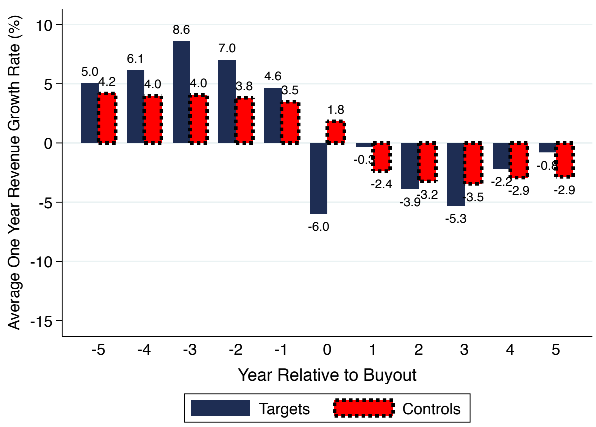
Notes: Figure plots cumulative changes for employment (panel A) and revenue (panel B) at target and control firms five years post buyout, normalized to year -1 relative to buyout year. Panel C shows cumulative revenue divided by cumulative employment.

[21] Prior literature (see Davis et al. (2014) online appendix) find a similar pattern of employment growth rates for target and control firms.

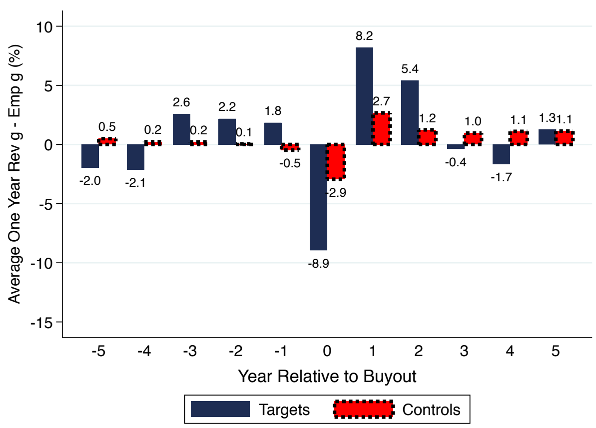
Figure C.30. Non Parametric: Changes in Employment, Revenue, and Labor Productivity at U.S. Target and Control Firms Pre and Post Buyout, PE Deals 1997-2018



(A) Employment g (yoy)



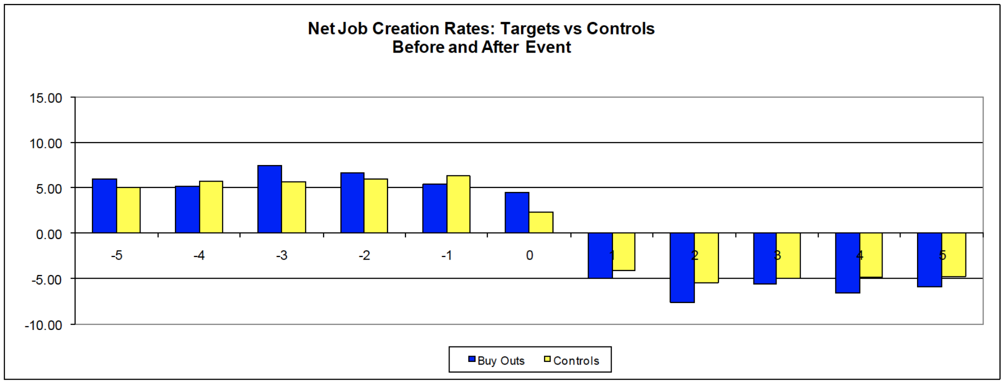
(B) Revenue g (yoy)



(C) Rev g (yoy) - Emp g (yoy)

Notes: Figures plot year over year growth rates in targets and controls five years pre and post buyout for employment (panel A), revenue (panel B), and revenue g minus employment g (panel C). Blue bars represent targets and red bars controls. Year 0 captures the effect of buyout.

Figure C.1: Employment Growth Rates before and after the Buyout Year, Targets and Controls Compared, Buyouts from 1980 to 2000



Notes: Source: Davis et al. (2014) Online Appendix.

C.2 Different Random Samples using Census Micro-Data

Table C.12. Estimated Coefficients for Difference in Difference, PE Deals 1997-2018

Dependent Variable:	Emp g (1)	Pay g (2)	Rev g (3)	Pay g-Emp g (4)	Rev g-Emp g (5)
			Random Sample 2		
Treatment × Post Buyout	-0.0247^{***}	-0.0243^{***}	-0.0269^{***}	0.0004	-0.0022
	(0.0099)	(0.0105)	(0.0081)	(0.0029)	(0.0079)
Observations	25,440,000	25,440,000	25,440,000	25,440,000	25,440,000
Adjusted R^2	0.0395	0.0561	0.0454	0.0101	0.0076
			Random Sample 3		
Treatment × Post Buyout	-0.0266^{***}	-0.0241^{**}	-0.0281^{***}	0.0025	-0.0015
	(0.0103)	(0.0106)	(0.0078)	(0.0026)	(0.0079)
Observations	25,430,000	25,430,000	25,430,000	25,430,000	25,430,000
Adjusted R^2	0.0362	0.0524	0.0422	0.0094	0.0081
			Random Sample 4		
Treatment × Post Buyout	-0.0223^{***}	-0.0211^{**}	-0.0254^{***}	0.0013	-0.0031
	(0.0084)	(0.0089)	(0.0077)	(0.0030)	(0.0075)
Observations	25,440,000	25,440,000	25,440,000	25,440,000	25,440,000
Adjusted R^2	0.0368	0.0541	0.0401	0.0096	0.0076
			Random Sample 5		
Treatment × Post Buyout	-0.0290^{***}	-0.0253^{***}	-0.0293^{***}	0.0037	-0.0003
	(0.0086)	(0.0091)	(0.0069)	(0.0029)	(0.0076)
Observations	25,450,000	25,450,000	25,450,000	25,450,000	25,450,000
Adjusted R^2	0.0378	0.0529	0.0415	0.0078	0.0077
Industry × Age × Size × Type × Transaction Year FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Lagged Firm g	Y	Y	Y	Y	Y
Weighted Emp t_0	Y	Y	Y	Y	Y

Notes: The table displays coefficients γ of the difference in difference specification:

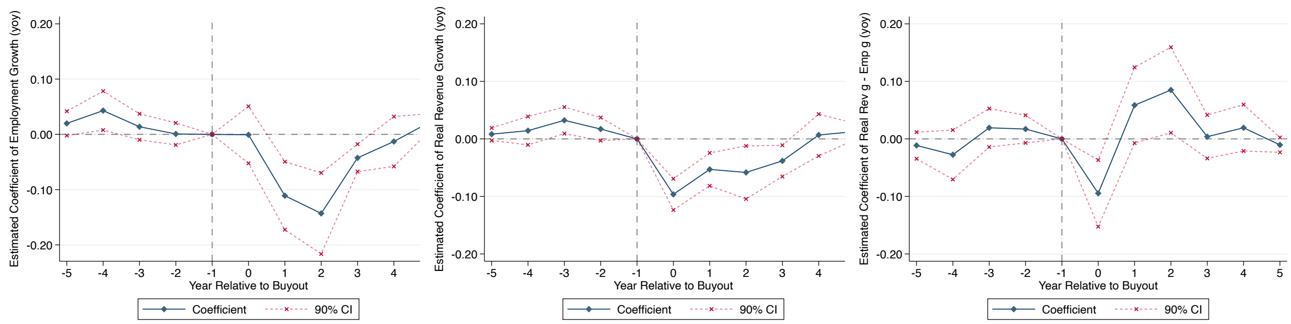
$$y_{it} = \alpha_t + \gamma(\text{PE}_i \times \text{Post}_{it}) + \sum_c \theta_c D_{cit} + \lambda_0 \text{LFIRM}_i + \varepsilon_{it}$$

D_{cit} are dummies for a fully saturated interacted fixed effects of firm characteristics: industry, age, size, type of unit, and buyout year. Regression estimates are weighted by employment in buyout year t_0. For robustness, regressions are also weighted by employment in year $t_0 - 3$ relative to buyout, and give similar results (not reported). Standard errors are clustered at the firm level to account for potential heterogeneity. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

C.3 Using Additional Controls

In addition to the lagged firm growth from period $t_0 - 3$ to $t_0 - 1$ relative to buyout used in figure 10, I also control for lagged one year revenue controls for revenue growth effects. Figure C.31 shows similar results for both versions of the difference in difference.

Figure C.31. Difference in Difference Estimated Coefficients γ_j Over Time Relative to Buyout Year, PE Deals 1997-2018



(A) Employment g **(B)** Revenue g **(C)** Rev g - Emp g

Dependent Variable:	Emp g (1)	Rev g (2)	Rev g-Emp g (3)
Treatment × Post Buyout	-0.0288^{*}	-0.0295^{***}	-0.0009
	(0.0152)	(0.0099)	(0.0123)
Industry × Age × Size × Type × Transaction Year FE	Y	Y	Y
Year FE	Y	Y	Y
Controls	Y	Y	Y
Weighted Emp t_0	Y	Y	Y
Observations	19,030,000	19,030,000	19,030,000
Adjusted R^2	0.0407	0.0556	0.0080
Dependent Variable Mean	0.0202	0.0251	0.0049

(D) Long Run Effects

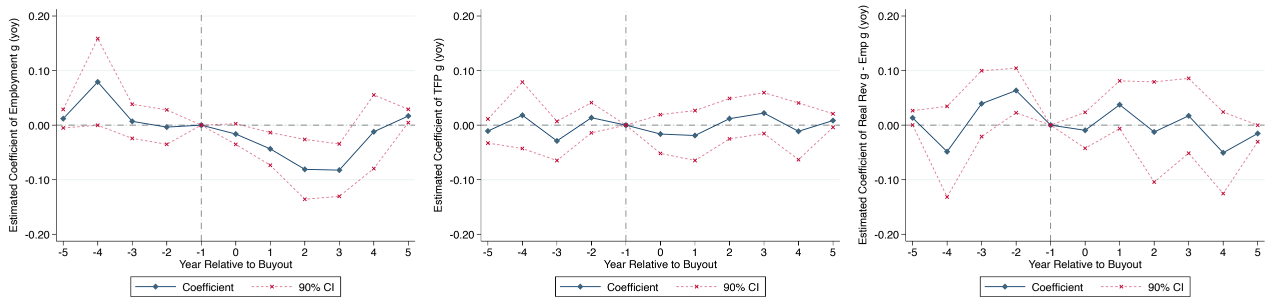
Notes: Panels A, B, and C show coefficients γ_j of the difference in difference specification 8:

$$y_{it} = \alpha_t + \sum_{j=-5, j\neq -1}^{j=+5} \gamma_j \left(\text{PE}_i \times \text{Buyout Year}_{it_0+j}\right) + \sum_c \theta_c D_{cit} + \lambda_0 \text{LFIRM}_i + \varepsilon_{it}$$

D_{cit} are dummies for a fully saturated interacted fixed effects of firm characteristics: industry, age, size, type of unit, and buyout year. Regression estimates are weighted by employment in buyout year t. Standard errors are clustered at the firm level. Dotted red lines show 90% confidence intervals. Table in panel D shows the long run effects γ. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

C.4 Manufacturing Targets

Figure C.32. Difference in Difference Estimated Coefficients γ_j for Manufacturing Firms Over Time Relative to Buyout Year, PE Deals 1997-2018



(A) Employment Growth **(B)** TFP Growth **(C)** Labor Productivity

Dependent Variable:	Emp g (1)	Pay g (2)	Rev g (3)	Rev g-Emp g (4)	$\Delta \log(TFP)$ (5)
Treatment × Post Buyout	-0.0076	-0.0082	-0.0183	-0.0107	0.0038
	(0.0080)	(0.0082)	(0.0119)	(0.0120)	(0.0055)
Industry × Age × Size × Type × Buyout Year FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Weighted Emp t_0	Y	Y	Y	Y	Y
Observations	4,106,000	4,106,000	4,106,000	4,106,000	4,106,000
Adjusted R^2	0.0373	0.0523	0.0369	0.0158	0.0110
Dependent Variable Mean	-0.0019	0.0059	0.0081	0.0100	0.0018

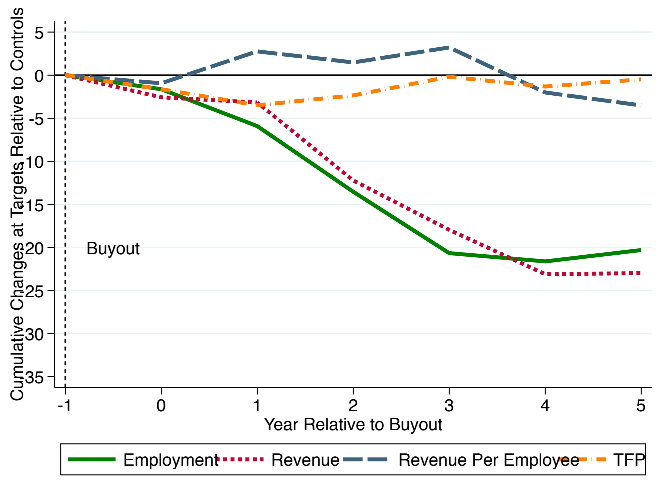
(D) Long Run Effects

Notes: Panels A, B, and C display coefficients γ_j of the difference in difference specification 8 for manufacturing firms. Panel D shows coefficient γ for the long run effects of outcome variables, where Post_{it} captures all years post buyout for firm i, and 0 otherwise. D_{cit} are dummies for a fully saturated interacted fixed effects of firm characteristics: industry, age, size, type of unit, and buyout year. Regression estimates are weighted by employment in buyout year t. Standard errors are clustered at the firm level to account for potential heterogeneity. Dotted red lines represent 90% confidence intervals. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Description of Measures. Using detailed cost metrics from the ASM and the CMF, I use total factor productivity measures constructed following the neoclassical production function. Establishment e's real gross ouput at time t, Y_{eit} can be written as a function of labor L_{eit}, capital K_{eit}, and materials M_{eit}: $Y_{eit} = A_{eit} \cdot F\Big(K_{eit}, L_{eit}, M_{eit}\Big)$. A_{eit} represents the plant level productivity (TFP). Following Baily, Hulten and Campbell (1992), $\ln \text{TFP}_{eit}$, the log of total factor productivity at the plant level is $\ln \text{TFP}_{eit} = \ln Y_{eit} - \alpha_K \ln K_{eit} - \alpha_L \ln L_{eit} - \alpha_M \ln M_{eit}$.[22] I aggregate $\ln \text{TFP}$ at the firm level using employment at establishments as

[22] I use the Census computed TFP measure, and confirm results with my own construction. Appendix C.4

Figure C.33. Cumulative Changes of Outcome Variables for Manufacturing Target Relative to Control Firms Over Time, Private Equity Deals 1997-2018



Notes: The figure cumulates difference in difference estimated coefficients γ_j from specification 8 for manufacturing firms over time relative to buyout year.

weights.

Operationally, plant level output is shipment plus change in finished and work-in-progress inventories, deflated by the four-digit industry-level shipment deflator. Capital is calculated separately for equipment and structures using the perpetual inventory method. Labor includes production and non-production worker hours. Materials include both, energy and other materials, deflated by their respective industry-level price indices. Factor elasticities are industry-level cost shares.

shows the results and appendix F.1 details construction of variables.

D Data Description

This section describes in detail the datasets used in the paper.
Preqin: Preqin is a dataset on alternative assets providing detailed information on investments in private markets across all asset classes: private equity (PE), venture capital (VC), hedge funds (HF), real estate (RE), infrastructure (INF). Preqin sources it's data mainly from FOIA requests and relationships with general partners/ funds. More information can be found on https://pro.preqin.com/. I use the Preqin portal instead of the Wharton Research Data Service (WRDS) to download the data, as the portal has more detailed information than the WRDS database.

Preqin has multiple tables, which can be mainly classified into "investors", "fund families", "funds", "performance", and "companies and deals". To clarify, "funds" refer to a PE fund, for example Blackstone Capital Partners VI and "fund families" refer to the PE fund family, for example Blackstone Group. I download all tables for the PE asset class category. In addition to the above mentioned main segments, Preqin also provides sub tables within each segment. This is tedious to get as one cannot download all these tables at once, and have to do it investor by investor. For example, for each investor, I download the "historical allocations", "fund portfolio", "fund family relationships", and "buyout deals exposure".

Next, I merge different tables of Preqin using investor, PE fund, PE fund family, and firm identifiers. This gives me linkages across the multiple players in private markets and helps me observe the entire chain of capital flow to the most granular level. Specifically, I observe CalPERs (LP) investing in Blackstone Capital Partners VI (PE fund) which belongs to Blackstone Group (PE fund family or GP), and the Blackstone Capital Partners VI fund buys Cordis, a medical device manufacture company (firm) based out of Florida in 2021.

On the deal side – between the sub PE fund and the firm, I observe detailed geographic and website identifiers of the portfolio companies. I manually did web searches and visited websites of firms, to fix data discrepancies in firm location (zip codes, states) and websites. The exact terms of the deal are sparsely populated and not needed for my analysis. Additionally, I obtain fund performance measures like IRR, geographic focus, strategy, fund size, industry focus, and management fee (sparse coverage).

The uniqueness of the data comes from it's granularity. First, I observe not only the relationships between the LP and GP which is mostly studied in previous literature, but also the linkages between LPs and PE funds within a PE fund family. This allows me to exploit variation within a GP across funds. Second, for a subset of LP-GP linkages, I observe the committed capital amounts, which is the amount committed by LPs to PE funds generally at the time of fund inception. This is extremely sensitive information. First, I observe this at the LP-sub PE fund level, and second, I can see the exact amount committed by the LP. Third, the data I have collected and cleaned spans across developed and emerging countries from 1976 to 2022, which makes it possible for me to expand this study across countries in future work.

For the purpose of this paper, I filter the deals where the country of the PE target is the U.S.

Revelio Labs: Revelio Labs is a private data provider tracking workforce at companies across countries. The data covers all public companies, and over 2 mn. private companies. Their main objective is to track hiring and offshoring of talent at a high frequency. Revelio sources its data from a variety of sources, such as, online professional profiles, job postings, published labor statistics by the government, social security administration, voter registration etc. The employment data starts in 2008 and is available on a monthly basis. More information can be found here: https://www.reveliolabs.com/. For this project, I have access to employment data from Revelio for PE targets in Preqin.

Standard Statistical Establishment Listing (SSEL): The SSEL is sourced from The Business Registrar (BR), which is the backbone of all Census administrative micro-data and economic surveys. The BR is a central repository maintained by the Census Bureau which tracks statistical and administrative records of all active employer business administrations having payroll during the past three years, or having an indication to hire in the future. It is the most current and compresensive database being maintained in the U.S. since 1972.

The SSEL has detailed information on establishment names and addresses including zip code and finer geographic identifiers such as the census tract and block-level. The smallest unit of observation is an establishment or a place of business. The SSEL also provides linkages across firms and employments over time. The data is continuously updated every year, and an annual snap-shot of establishments is made available to the researcher. More information about the BR and SSEL can be found in the following Center for Economic Studies (CES) working papers: https://www2.census.gov/ces/wp/2016/CES-WP-16-17.pdf and https://www2.census.gov/ces/wp/2002/CES-WP-02-17.pdf.

Revenue Enhanced Longitudinal Business Database (LBDREV): The LBD covers all business establishments in the U.S. private non-farm sector with at least one paid employee (Jarmin and Miranda (2002)). An establishment is the lowest level of aggregation in the LBD. The companion product of the LBD for public use is the Business Dynamics Statistics (BDS).

The database links establishments and firms over time, tracking entry and exit of establishments, employment, pay, and detailed industry and state codes. This enables accurate measurement of changes in business activity. This is especially crucial since firms often change their Employer Identification Number (EIN) while filing taxes, or entites change because of merger or re-organization. The main contribution of the revised LBD is to create time consistent longitudinal establishment and firm identifiers, especially for small, single-establishment firms which had broken links in prior versions. The Census Bureau re-programmed and re-examined the original LBD for such inconsistencies, and republished a revenue enhanced LBD (LBDREV) in September 2020.

In this paper, I use the revised LBD. I will refer to LBDREV as LBD. A good reference for the LBD and the changes made is https://www2.census.gov/ces/wp/2021/CES-WP-21-08.pdf.

Census of Manufactures (CMF): The Economic Censuses provide more detailed statistics on employment, costs, capital expenditures, value of shipments, and revenues. The CMF covers all manufacturing establishments and firms (NAICS Sector 31-33) with at least one paid employee. The Census is conducted every five years - those ending in '2 and '7. More information on the CMF can be found here: https://www.census.gov/data/tables/2017/econ/economic-census/naics-sector-31-33.html.

Annual Survey of Manufactures (ASM): The ASM provides detailed estimates of statistics for manufacturing establishments and firms with at least one paid employee. The manufacturing firms in the survey are sampled from the CMF, which covers the universe of manufacturing firms in the U.S. The ASM is conducted annually except for years ending in '2 and '7, when the CMF is carried out.

The ASM provides statistics on employment, payroll, detailed cost measures on labor, materials consumed, and energy, capital expenditures, and value of shipments. More details about the data are here: https://www.census.gov/programs-surveys/asm/about.html.

Longitudinal Employer-Household Dynamics (LEHD): The LEHD database provides a comprehensive view of workers, employers, and their interactions in the U.S. economy by location. The LEHD infrastructure files are structured in various components, described below. Data are sourced from various state agencies and enhanced from administrative data, economic and demographic censuses, and surveys. The main advantage of the LEHD is that it allows the researcher to track worker-firm relationships over time via time consistent identifiers. It is important to note that worker-establishment-firm relationships are not made available by states[23], hence all the analysis is done at the worker-firm level.

All states do not share their data with Census researchers. I have access to 27 states: Arizona, Colorado, Connecticut, Delaware, Iowa, Indiana, Kansas, Massachusetts, Maryland, Maine, North Dakota, New Jersey, New Mexico, Nevada, New York, Ohio, Oklahoma, Pennsylvanaia, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Washington, Wisconsin, Wyoming. The main corpses are: (1) Employer Characteristics File (ECF), Employment History Files (EHF), Unit-to-Worker Impute (U2W), and Geocoded Address List (GAL). For this paper, I use the ECF Title 26 and EHF files.

1. **ECF Title 26:** The ECF Files consolidate LEHD employer micro-data on firm size, location, industry, etc. These files contain variables from the LBD which can be used to construct the firm identiers in the LBD. This is of essential as the firm identiers in the LBD and LEHD are different.

2. **EHF:** The EHF Files store the complete history of employment in the state over time. Specifically, there exists an observation for each individual that appears in the wage records of some firm or establishment. In other words, there exists one observation per employee-employer combination for a job in that state-year.

A detailed and very good reference for the LEHD is here: https://www2.census.gov/ces/wp/2018/CES-WP-18-27R.pdf.

Public Pensions Database (PPD): The PPD contains detailed annual data on the largest state and local pension plans in the U.S. The data ranges from 2001 to 2020 and covers 210 plans. The statistics include balance sheet variables like assets, liabilities, and funded positions, plan contrbutions, asset allocations, investment returns and horizon. More information can be found here: https://publicplansdata.org/public-plans-database/.

FOIA Requests: The public pensions database has good coverage of public pension fundamentals from 2001. I supplement data on public pension assets and liabilities going back to 1983 from FOIA requests to individual pensions.

Union Stats and BLS: Union Stats is the Union Membership and Coverage Database providing public and private sector labor union membership and density statistics. Union statistics are available by state, metropolitan area, and industry from 1983 to 2021. I also verify and the union data from the Current Population Survey (CPS) releases on the BLS website. More information on union stats can be found here: http://www.unionstats.com.

[23]Except for the state of Minnesota, which I do not have access to.

E Sample Construction

E.1 Cleaning Preqin and Merging Across Preqin Datasets

E.1.1 Investor Files

The main investor files contains investor characteristics such as name, type indicating whether it is a public pension, private pension, sovereign wealth fund, family office, insurance company, or a bank, assets under management, allocation to private asset classes, and geographic location.

E.1.2 Fund Portfolio Files

This data consists of investor-fund pairs. I observe the connections between investors and funds, including detailed information on investor and fund characteristics. I get industry focus, fund domicilies, fund vintage, and parent PE fund connections. Further, I see the dollar amounts of committed capitals between the investor and the fund. The main advantage of the study is that I observe connections between investor and sub PE fund.

E.1.3 Deals and Portfolio Companies

The "deals" tables depicts investments made by PE funds within a fund family to firms. The firms are also known as portfolio companies. The tables have detailed geographic identifiers for the firms. Value of deals is not well populated. This is not much of a concern as the main focus of the analysis is the connections between funds and firms.

E.1.4 Cleaning and Merging

I apply the following cleaning approach:

1. In Step 1, I clean the Preqin data on portfolio companies. In many instances, the states are coded incorrectly. Preqin also has two fields of states and addresses, which don't match at all times. For instance, a company might have a headquarter office and a regional office which can be a reason for discrepancy. For companies with inconsistent states and addresses across fields, I manually search the websites of individual companies and clean the states.

2. I apply two main filters. First, I keep only those targets and deals which have at least one of the asset class designations as "PE".[24] Second, I keep targets in the U.S..

[24] A deal can have more than one asset class designation - this can happen when a fund focuses on more than one asset class.

3. I standardize names and addresses of all companies in Preqin.

4. I drop observations where the deal date is not available.

5. In few cases, an investor-fund pair might be involved in multiple deals with the same target in multiple years. This is can generally happen when one PE fund sells the target to another PE fund in a secondary market. To cleanly identify the effects of buyouts, I consider the first buyout. Correspondingly, I only consider real outcome effects with respect to the first deal before the second deal. In the same spirit, in case there are multiple buyout deals for the same company in the same year, I consider the first deal by date. This can happen if different establishments within a firm undergo an LBO by different PE funds. These are very few cases and does not alter the result.

For the second part of the paper, I only consider deals which have a LP or GP connections associated with them - which is majority of the matched firms: 8,500 out of 9,300.

I merge tables from Section E.1.1, E.1.2, and E.1.3 to get the investor - PE fund (also referred to as “fund family”) - sub PE fund - firm (or “portfolio company”) chain. In order to study the effects on firms post buyout, and heterogeneity in outcomes due to funds and investors, I merge this chain with Census datasets described below.

E.2 Merging Private Equity Buyouts with SSEL

SSEL has names and exact addresses of all establishments in the U.S. Each establishment in the Census micro data is linked to a firm, so I have access to the full establishment-firm heirarchial structure in the U.S. The SSEL is the main dataset which is used to connect outside datasets with the Census Bureau micro-data. I merge firms in Preqin with SSEL based on state, name, city, and address match. The objective is to match the buyout targets with firms in the Census, which can be either multi- or single-unit. In a few cases, it might happen that more than one establishment in the same Census firm identifier is part of different buyout deals. I drop them as it is not possible to ascertain the unmatched establishments of the Census firm belong to which target. I follow a step-by-step methodological approach to merge private equity targets with the Census. I perform this match within the primary state of the firm identified from Preqin, and then combine the state-by-state merged results.

1. From the output of Section E.1, I extract a list of unique PE targets in the U.S. along with their full name, address, other geographic identifiers, and deal dates. I consider the first deal date as the point of reference for targets involved in multiple deals. Additionally, one target might have two identifiers in the Preqin data. This might happen if the company changed its structure and it’s given a new identifier (few

cases). I consider only one of the identifiers to get a unique set of target names and identifiers, which is necessary for merge with the Census micro data. I end up with 26,267 unique PE targets in the U.S. from 1976 to 2021.

2. The SSEL establishment-firm data is sourced from the Business Register (BR). I use the SSEL yearly files from 1976 to 2019 for merging the targets with the Census micro data. Specifically, I match the targets to the SSEL file one year before the buyout deal.[25] I consider a year before as the targets might undergo a name or entity change, or might dissolve some years post buyout. The number of establishments in the SSEL range from 5.2 mn. in 1976 to 9 mn. in 2019, and the number of firms from 4.5 mn. in 1976 to 7 mn. in 2019. I take the following cleaning approach:

   (a) I consider the state code from CBP. This state code is available for most establishments. This code also matches with state fips codes based on the physical and mailing addresses for majority of the establishments. When the state code from CBP is not available I consider the physical state code followed by the mailing state code. I do not consider establishments which do not have a state associated to them for merge accuracy.

   (b) I standardize names and addresses of all establishments in the Census. I consider both the main name ("name1") and the pseudo name ("name2"), and the street and physical addresses. I standardize both versions of the names and addresses. For merge accuracy, I do not consider establishments which have no name.[26]

3. I match on exact state and names, exact state and addresses. I do multiple checks to make sure the match is accurate. First, for the address matches, I check for zip code and city matches. I do not impose stringent restrictions for city matches. To get accurate matches, I make sure the city in the Preqin data approximately matches the city of at least one establishment in the Census data. Second, I omit all "PO Box" matches.

4. It might be the case that one portfolio company is matched to multiple Census firm identifiers. This can happen for two reasons. First, when multiple firms have the same address, for instance in a large complex. Second, when a firm has different Census firm identifiers but the same headquarter address for its various subsidiaries. This gives false matches. In such a situation, ideally I would want to find the closest Census-firm subsidiary to the target. However, it is not feasible to distinguish between the two

[25] I redo the match using two years before the deal, it does not change the result.

[26] More information on the variable can be found here: https://www2.census.gov/ces/wp/2021/CES-WP-21-08.pdf.

cases. To clean the cleanest possible sample, I drop cases where one target is matched to multiple firms within a state.

5. The reverse might also be possible, in which multiple targets might be matched to the same Census firm. This might happen when different establishments of a firm are parts of different buyout deals. These situations are rare. In such situations, I am unable to identify the parent firm from the buyout data for the unmatched establishments in the SSEL. To get a clean sample, I omit such buyout targets with multiple matches.

6. Next, I combine all the links between targets and matched establishments in the SSEL year files.

E.3 Merging Private Equity Buyouts with Revenue Enhanced LBD

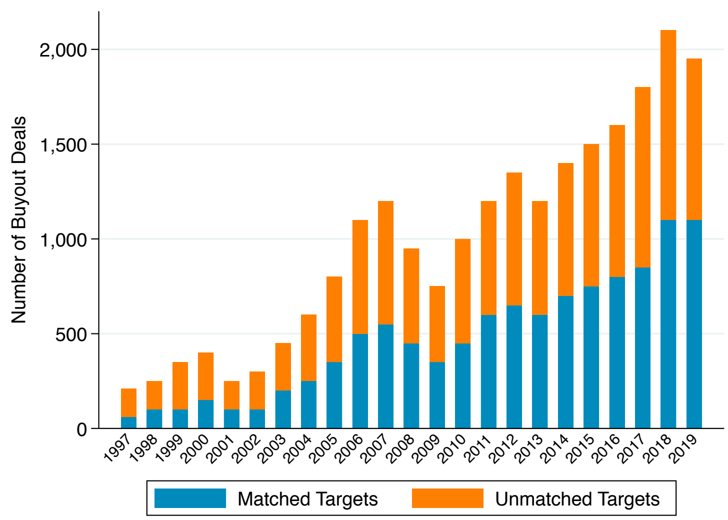
I combine all the LBD revised establishment year files. Next, I merge the output of Section E.2 with the appended LBD files by year and establishment identifier.

In few cases, Census firm identifiers in the SSEL and LBD do not match. I drop these to maintain consistency across datasets. In the end, the matched sample is such that the firm identifiers have a one to one mapping across datasets.

Next, I pull all the unmatched establishments of matched firms between Preqin and SSEL. I get a clean match of 11,680 targets across 52 states in buyout deals from 1976 to 2019.

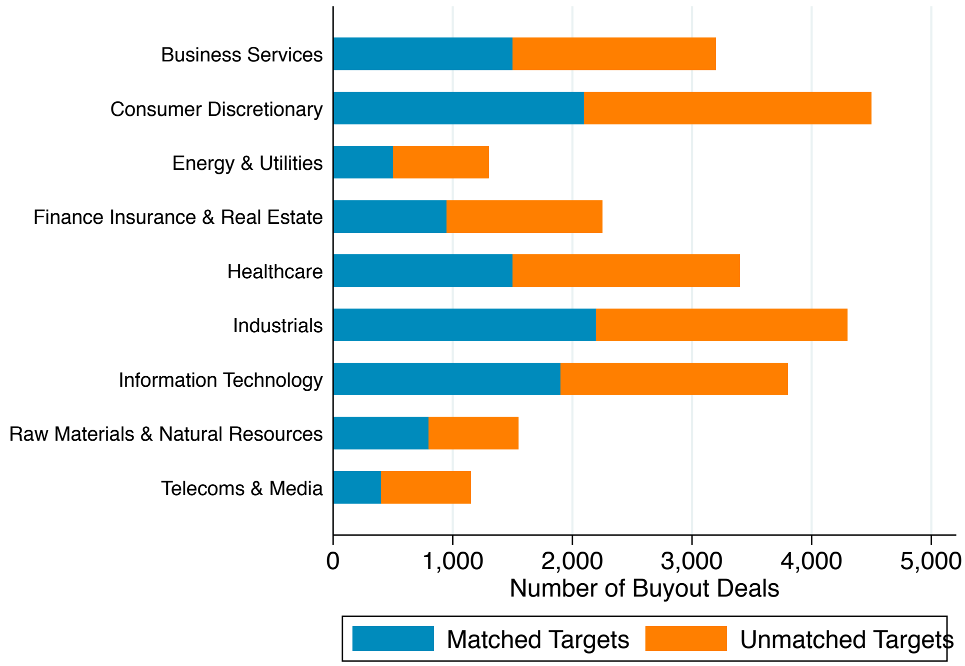
Figure E.34 shows the matched and unmatched targets by year, Figure E.35 shows by industry and state. The stringent match methodology explains the conservative matches.

Figure E.34. Matched and Unmatched U.S. Target Companies Over Time

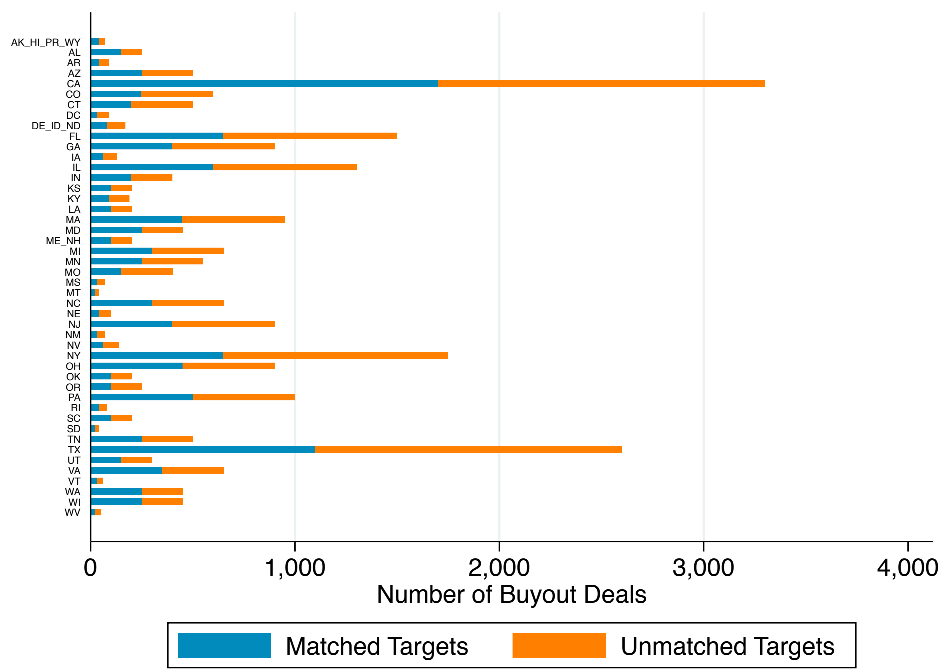


Notes: The figure plots the number of buyout deals involving U.S. target companies over years from 1997 to 2019. Matches prior to 1997 are not disclosed from the Census yet. The buyout deals are sourced from Preqin. Blue bars represent the number of targets matched with Census micro-data, and orange bars represent unmatched targets. I match 11,850 target firms from 1976 to 2019. The unmatched firms are due to a strict merge criteria considering firm characteristics one year pre-buyout to get a clean match, and reduce noise from possible incorrect addresses in external datasets.

Figure E.35. Matched and Unmatched Targets by Industry and State



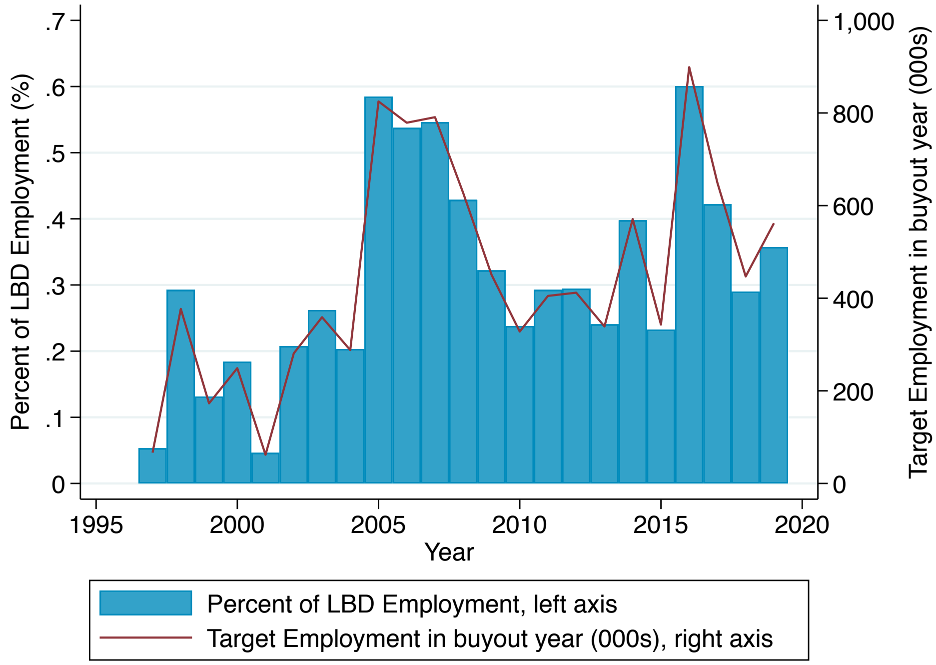
(A) By Target Industry



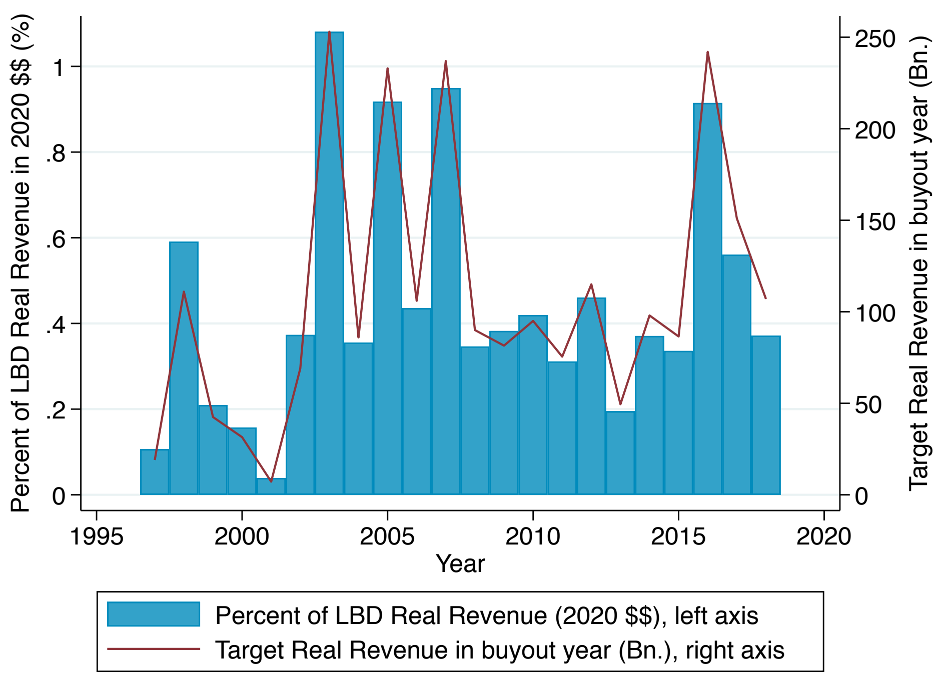
(B) By Target State

Notes: The figures plot total number of buyout deals involving U.S. PE target companies across industries (panel A) and states (panel B). PE buyout deals from 1979 to 2019. Blue bars represent number of targets matched with Census micro-data, and orange bars represent unmatched targets. Some states are grouped together to meet Census disclosure requirements. Buyout deals are sourced from Preqin.

Figure E.36. U.S. PE Target Employment (Revenue) as a Percentage of Total Non-Farm Payroll Employment (Revenue) in Buyout Year



(A) Employment



(B) Revenue

Notes: The figures plot employment and revenue of U.S. PE targets matched with the Census micro-data in the year of buyout. Panel A shows employment and panel B shows real revenue in 2020 dollars. Blue bars plot target employment (revenue) as a percent of total LBD employment (revenue) over time on the left axis. The red line shows total matched employment (revenue) in raw numbers on the right axis. The figure represents numbers as of the buyout year.

E.4 Merging Private Equity Buyouts with ASM and CMF

This section describes the merge of private equity buyouts with the Census of Manufactures (CMF) which exists for years ending in $'2$ and $'7$ and the Annual Survey of Manufactures (ASM), which is carried out every year other than $'2$ and $'7$.

With the revised LBD, there exists an LBDREV linkage file which connects LBDREV identifiers to the Censuses and survey data. I use this link file as a bridge to connect LBD with the ASM and CMF. This is especially useful as there are multiple versions of the establishment identifier in the LBD.

I use the main files from the CMF and ASM which have detailed information on establishment-level costs and sales. Additionally, the Census has ASM-CMF total factor productivity (TFP) files which computes TFP at the establishment level. These measures were originally used in Foster, Grim and Haltiwanger (2014). The bridge file is used to merge both these datasets to the LBD.

I also merge the NBER-CES Manufacturing Database to the ASM and CMF via four-digit SIC codes and years. For this purpose, it is important to get a comprehensive link of the establishments with the industry codes. I use the industry codes in the LBD as the base, and supplement it with industry codes in the ASM and CMF when missing. The coverage of the LBD industry codes is better than that of ASM and CMF.

E.5 Merging Private Equity Buyouts with LEHD

This section describes the merge process for private equity buyout transactions with worker-level data obtained from the LEHD. The first step is to merge the firm level LBDREV file with the LEHD. The LBDREV can only be merged with the LEHD at the firm level. Only the state of Minnesota has establishment-worker level data, which I do not have access to. Other states only for firm-worker level pay.

The Employment History Files (EHF) contain worker level information at the establishment level. The LBD and LEHD firm and establishment identifiers are different. To merge the EHF files with the Preqin-LBD merged dataset, I use the Employer Characteristics Title 26 Files (ECF T26). The ECF T26 files have the firm identifier which is used to link the LBDREV and EHF files. The merge process is described below in detail.

First, I get both the Preqin-LBD merged file and the ECF T26 files to a firm-year level. Since the LEHD files are organized by state, I subset the Preqin-LBD data to different states based on the headquarter state of the firm. I merge the two files on firm, year, and state. Next, I append all the LBDREV-LEHD links for firms by year over all 27 states.

Finally, I pull all the worker-level data for the LBDREV merged LEHD identifiers from the Employment History Files (EHF).

E.6 Merging Private Equity Buyouts with Public Pensions Database

First, I supplement financials from the Public Pensions Data (PPD) with FOIA requests from 75 individual public pensions. I complement the data going back until 1983 for these pensions.

I manually match U.S. public pension fund investors in the private equity dataset to public pensions in the PPD and FOIA combined dataset by name. I manually search the websites of each state pension. Often times, a state pension will have different subsidiaries for teachers, employees, firemen maintaining separate balance sheets. I match financials and individual PE investments on the subsidiary – i.e., I match California Teachers' financials with California Teacher's individual PE investments. In cases where I do not have the exact subsidiary, I match financials of the parent plan, e.g. Colorado Public Employee Retirement Association for its Local, State, and School division.

F Variable Construction

This section describes construction of variables at the establishment level e and the firm level i.

F.1 Production Function Variables

Establishment Level.
The neoclassical production function, where Y_{eit} is the real gross ouput for establishment e, firm i, and time t can be written as a function of K_{eit}, L_{eit}, and M_{eit}, representing capital, labor, and material inputs respectively.

$$Y_{eit} = F(K_{eit}, L_{eit}, M_{eit}) \tag{10}$$

The production function 10 is the main equation to calculate total factor productivity (TFP). Following Baily et al. (1992), $\ln \text{TFP}_{eit}$ representing plant-level log of total factor productivity can be written as,

$$\ln \text{TFP}_{eit} = \ln Y_{eit} - \alpha_K \ln K_{eit} - \alpha_L \ln L_{eit} - \alpha_M \ln M_{eit} \tag{11}$$

I define each of the inputs in equation 11 below. Definitions of these variables are standard in the literature, and are drawn from Abraham and White (2006), Giroud (2013), and Davis et al. (2014).

Output. Real output Y_{eit} is the total value of shipments, change in finished goods inventories and work-in-progress inventories from beginning to the end of year, deflated by the four-digit shipment deflator.

$$\begin{aligned} Y_{eit} &= \frac{\text{TVS}_{eit} + (\text{TIE}_{eit} - \text{TIB}_{eit}) + (\text{WIE}_{eit} - \text{WIB}_{eit})}{\text{PISHIP}_t}, \quad \text{if } Y_{eit} > 0 \\ Y_{eit} &= \frac{\text{TVS}_{eit}}{\text{PISHIP}_t}, \quad \text{otherwise} \end{aligned} \tag{12}$$

where, TVS_{eit} is the total value of shipments, TIE_{eit} and TIB_{eit} is the total value of finished goods inventories at the end and beginning of the year respectively, WIE_{eit} and WIB_{eit} is the work-in-progress inventories at the end and beginning of the year respectively. All components are in nominal dollar terms. These are deflated by PISHIP_t which is the four-digit industry level shipments deflator from the NBER-CES Manufacturing Database.

Capital Stock. K_{eit} is the total value of real capital stock including investments during the year. Capital stock is not available for most of the years of the ASM and CMF. The Annual Survey asked questions related to buildings (structures) and machinery (equipment) separately until 1985 and upto the 1992 Census. From 1997 onwards, Census asked questions about total assets at the end of year, i.e., the sum of building and machinery assets. I follow the perpetual inventory method to impute capital stock for intermediary years.

$$K_{eit} = K_{eit-1} \times (1 - \delta_{it}) + I_{eit} \tag{13}$$

K_{eit} represents capital stock in period t. δ_{it} is the depreciation rate between $t-1$ and t, and I_{eit} is investments between $t-1$ and t. In terms of implementation, I calculate the capital stock separately for machinery and structures until 1985.

$$\text{KEQ}_{eit} = \text{KEQ}_{eit-1} \cdot (1 - \text{EQDPR}_{it}) + \frac{\text{NM}_{eit}}{\text{PIINVE}} \tag{14}$$

$$\text{KST}_{eit} = \text{KST}_{eit-1} \cdot (1 - \text{STDPR}_{it}) + \frac{\text{NB}_{eit}}{\text{PIINVS}} \tag{15}$$

where, KEQ_{eit} and KST_{eit} represent machinery and structures respectively, EQDPR_{it} and STDPR_{eit} are depreciation rates, NM_{eit} and NB_{eit} are nominal dollar investments, and PIINVE and PIINVS are deflators for machinery and buildings respectively.

From 1997, I use total capital which is the sum of nominal book value of machinery and buildings.

$$\mathrm{K}_{eit} = \mathrm{K}_{eit-1} \cdot (1 - \mathrm{EQDPR}_{it}) + \frac{\mathrm{TCE}_{eit}}{\mathrm{PIINVE}} \tag{16}$$

TCE_{eit} is the total capital expenditure between $t-1$ and t.

To use the perpetual inventory method, one needs to initialize capital stocks. I multiply the nominal value of machinery (buildings) with the ratio of the industry level nominal net capital stocks to the industry level real gross capital stocks for machinery (buildings), and deflate it by the appropriate industry level deflator.

$$\mathrm{KEQ}_{eit}^{initial} = \frac{\mathrm{MAE}_{eit} \cdot (\mathrm{NKCEQ}_{eit}/\mathrm{GKHEQ}_{eit})}{\mathrm{PIINVE}} \tag{17}$$

$$\mathrm{KST}_{eit}^{initial} = \frac{\mathrm{BAE}_{eit} \cdot (\mathrm{NKCST}_{eit}/\mathrm{GKHST}_{eit})}{\mathrm{PIINVS}} \tag{18}$$

$$\mathrm{K}_{eit}^{initial} = \frac{\mathrm{TAE}_{eit} \cdot (\mathrm{NKCEQ}_{eit}/\mathrm{GKHEQ}_{eit})}{\mathrm{PIINVE}} \tag{19}$$

MAE_{eit}, BAE_{eit}, and TAE_{eit} are the nominal book values for machinery, buildings, and total assets. NKCEQ_{it} and NKCST_{it} are the two-digit industry level nominal net capital stocks for equipment and structures respectively, while GKHEQ_{it} and GKHST_{it} are the gross capital stocks. Combining Equations 14-16 and 17-19, I can interate forward and backward to calculate capital stock. In some cases, capital stock cannot be calculated. A detailed description in given in the Data Appendix of Abraham and White (2006).

Labor. Labor L_{eit} is measured as "production worker-equivalent hours", which includes both production hours and non-production hours. The total number of hours worked by production workers PH_{eit} is multiplied by the ratio of total wages including supplementary labor costs SW_{eit} and wages of production workers WW_{eit}. The exact specification is drawn from Foster et al. (2014).

$$\begin{aligned} \mathrm{TH}_{eit} &= \frac{\mathrm{PH}_{eit} \times \mathrm{SW}_{eit}}{\mathrm{WW}_{eit}}, \quad \text{if } \mathrm{SW}_{eit} > 0,\ \mathrm{WW}_{eit} > 0 \\ \mathrm{TH}_{eit} &= \mathrm{PH}_{eit}, \quad \text{otherwise} \end{aligned} \tag{20}$$

Materials. M_{eit} is the real value of material inputs. The nominal value of materials CM_{eit} is the sum of total cost materials and parts CP_{eit}, cost of resales CR_{eit}, total cost of contract work done for the establishment by others CW_{eit}, cost of purchased electricity EE_{eit}, and cost of fuels CF_{eit}.

$$\mathrm{CM}_{eit} = \underbrace{\mathrm{CP}_{eit} + \mathrm{CR}_{eit} + \mathrm{CW}_{eit}}_{\equiv \mathrm{NE}_{eit}} + \underbrace{\mathrm{EE}_{eit} + \mathrm{CF}_{eit}}_{\equiv \mathrm{E}_{eit}} \tag{21}$$

The first three components correspond to establishment-level non-energy material costs NE_{eit}, and the last two components are establishment-level energy costs E_{eit}. I deflate the two components by the NBER-CES four-digit industry-level materials deflator PIMAT_t and the industry-level energy deflator PIEN_t, to get the real total cost of materials M_{eit} at the establishment-year level. The resulting value is in 1997 dollars.

$$\mathrm{M}_{eit} = \frac{\mathrm{CP}_{eit} + \mathrm{CR}_{eit} + \mathrm{CW}_{eit}}{\mathrm{PIMAT}_t} + \frac{\mathrm{EE}_{eit} + \mathrm{CF}_{eit}}{\mathrm{PIEN}_t} \tag{22}$$

Elasticities. α_K, α_L, and α_M are elasticites which are four-digit SIC industry cost shares at each time. Total cost is the total sum of expenditure on equipments and plants, pay towards labor, and material costs. α_K is the share of expenditure on capital, α_L is the share of expenditure on labor, and α_M is the share of expenditure on materials (including energy), all as a ratio of total costs. Since industry cost shares are noisy, divisional cost shares are used, i.e., the average between t and $t-1$ cost shares for each industry (Syverson (2011)). A detailed explanation is given in Appendix B of Foster et al. (2014).

Post obtaining the above inputs, one can calculate plant-level TFP using equation 11 for plants with positive input and output values.

Total Costs. Total costs TC_{eit} at the plant level is defined as the sum of all real labor and material costs, including energy.

$$TC_{eit} = L_{eit} + M_{eit} \tag{23}$$

M_{eit} are the same as defined above. L_{eit} is now the total labor cost in real 1997 dollar terms. It includes total wages and salaries towards all workers including non-production, and both leased and non-leased workers. The nominal expenditure SW_{eit} is deflated by the non-energy materials deflator PIMAT.

Profits. Real profits π_{eit} is total value of shipments post subtracting total costs TC_{eit}, scaled by shipments.

$$\pi_{eit} = \frac{\mathrm{TVS}_{eit} - \mathrm{TC}_{eit}}{\mathrm{TVS}_{eit}} \tag{24}$$

Firm Level.

$$\pi_{it} = \sum_e w_{eit}\pi_{eit} \tag{25}$$

where w_{eit} is employment at establishment e in year t. In few cases, the employment is 0. In such cases, I take the unweighted sum and mean respectively.