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

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(Link to most updated version)

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Abstract

I study the effects of private equity (PE) buyouts on labor productivity using a novel micro-data on investments in PE funds and PE buyout deals, combined with confidential Census data. I show that while PE increased productivity at target firms until 2011, it substantially decreased productivity post 2011. In the time series, the decrease in labor productivity is correlated with an increase in capital from the most underfunded public pensions. In the cross-section, I show that firms financed predominantly by the most underfunded public pensions experience a -5.2% annual change in labor productivity, as compared to firms financed by other investors which experience a +5.2% annual change. Firms supported by low quality PE funds face productivity decreases. The key mechanism is the notion of *desperate capital*, where the most underfunded public pensions allocate capital to low quality GPs, and realize lower PE returns. I introduce a novel instrument of public unionization rates to establish support for underfunded positions causing selection into low quality GPs, which ultimately leads to capital misallocation within private markets.

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1 Introduction

Private capital markets have grown tremendously over the last two decades, with $5.6 tn. in North America as of 2021. Private capital markets, includes private equity (PE), real estate, infrastructure, private debt, and natural resource investments. PE is two-thirds of private capital. The number of PE backed U.S. firms has increased by 106% from 2006 to 2020, while the number of publicly traded companies has decreased by 46% from 1996 to 2020. Approximately 11.7 mn. employees worked at firms targeted by PE in 2020.

However, the economic effects of PE are still controversial. On one side, Brendan Barber, General Secretary of Trade Union Congress 2007 refers to PE funds as "casino capitalists" who enjoy personal windfalls from deals.[1] On the other hand, American Investment Council advocates that PE supports small business investments and jobs.[2] In this paper, I will reassess this evidence by combining rich micro-data on PE buyout, firms outcomes, and end investors.

I ask two main questions. First, what are the effects of private equity buyouts on employment, revenue, and labor productivity at firms in which PE funds invest (target firms). Second, does the source of PE capital play a role in explaining these employment and productivity effects. I find that underfunded U.S. public pensions occupy a unique position among investors in PE funds. Desperately in need of 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)). The most underfunded pensions end up allocating capital to lower quality PE funds, which decreases productivity at firms, and leads to inefficient capital allocation.

I compile a novel micro-data on private equity buyouts including detailed investments by institutional investors (e.g., CalPERs) in PE 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 PE fund to the ultimate recipient. Next, I merge these PE transactions with the Census Bureau micro-data to track 9,300 PE targets from 1979 to 2019 over time. I also build a sample of control firms that are comparable to PE targets but not bought by PE. The control firms are constructed based on a granular match of industry, firm size and age, multi-unit status, and buyout year, following Davis, Haltiwanger, Handley,

[1] Refer here. Another evidence is in article "Why work has failed us: Because companies aren't sharing the profits" which mentions that Toys "R" Us employees were expected to stop working and apply for unemployment (link).

[2] For discussion, refer to Investment Council site (link).

Jarmin, Lerner and Miranda (2014). 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 study real effects of PE investments, with of focus on *labor productivity* considering all U.S. target firms in my sample which underwent a PE buyout from 1997 to 2018.[3] I track both target and control firms five years before and after buyout. I find that five years post buyout, employment at targets declines by 23.8% relative to control firms, revenue decreases by 23.2%, and labor productivity declines by 0.4%. For the average target, this corresponds to a loss of 405 jobs, $132 mn. drop in total revenue, and a $1,600 drop in revenue per employee post buyout. This result shows that even though employees are laid off and PE firm restructuring substantially decreases revenue, there are no efficiency gains as measured by labor productivity. Studying employment effects for PE deals from a longer time period, i.e. 1979 to 2018, I find a -29.5% five year cumulative change in employment post buyout. I find similar decreases in employment at target firms from another data provider, Revelio.

For firms in the manufacturing sector, I also construct *total factor productivity* (TFP) using detailed cost and factor input data from the Census of Manufactures (CMF) and the Annual Survey of Manufactures (ASM). First, I find similar employment and revenue declines as for all targets, -20.3% and -23% respectively relative to controls five years post buyout. Second, I continue to find no significant improvements in productivity, measured either by TFP (-0.5%) or labor productivity (-3.5%).

The null result for productivity in the full sample masks an important change in the time series. For PE deals from 1999 to 2011, I find a +7.3% two year cumulative productivity change post buyout.[4] My estimates are similar to Davis, Haltiwanger, Handley, Lerner, Lipsius and Miranda (2019) which finds a +7.5% two year productivity gain for the same time period. For PE deals from 2011 to 2018, I find a -5.4% two year productivity change. Combining both the periods together, I find subdued two year productivity gains of +2.8% for PE deals from 1997 to 2018, and a five year cumulative change of -0.4%. The insignificant labor productivity effects from 1997 to 2018 are driven by negative effects in the second half of the sample period.

The near causal evidence of a decrease in productivity due to PE investments coincides with a rise in the share of PE capital sourced from underfunded pensions. Capital committed

[3]Labor productivity measures are available from 1997 to 2018.

[4]Considering firms continuing for at least two years, I find a two year cumulative productivity gain of +8.7% for PE deals from 1999 to 2011.

by the most underfunded public pensions rose three fold, from 5.2% of all capital to PE funds in 2001 to 15.6% in 2018. This suggestive evidence motivates the cross-sectional results in the second part of the paper.

In the second part of the paper, I show that characteristics of PE investors (Limited Partners or LPs) and PE fund families (General Partners or GPs) correlate with real outcomes at PE target firms. Among LPs, public pensions represent the largest investor type, accounting for 31.3% of all investors and contributing 67% of the capital to PE funds.[5] On average, 20 LPs commit capital to a PE fund, and 1.4 funds finance a target. In the first step, I identify the dominant LP 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 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 based on one minus the ratio of assets to liabilities. I show that target firms whose dominant source of PE 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 PE capital in a deal is sourced from underfunded pensions, the larger the subsequent productivity loss of the target.

Since GPs and not LPs determine the investments that a PE fund makes, how can the source of LP capital matter for firm outcomes? Capital from LPs flows to targets via GPs. Differences in labor productivity outcomes at targets driven by LPs correlate with differences in GPs. I use a size-based measure of GP quality following the mutual fund literature (Berk and van Binsbergen (2015)). 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"). 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.

Targets financed by the lowest quality GPs experience largest productivity declines. For

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

instance, firms supported by GPs in the bottom 25th quality percentile, experience a -2.9% significant annual labor productivity change as compared to firms in the top 75th percentile which face a +1.4% insignificant productivity change. The negative productivity effects are larger the farther down the GP quality distribution one goes. Decreasing efficiency along the GP quality distribution is consistent with aggregate decreasing returns to scale in the PE industry. The lower quality GPs decrease revenue more than employment at firms thereby substantially decreasing productivity. I show evidence that lower quality GPs cause significant productivity declines post buyout by comparing performance of target firms by differing GP qualities. To compare similar targets but differing on GP quality, I control for granular industries, firm age and size categories, and type of firm characteristics of target firms. However, I cannot entirely rule out selection by different GPs for different investment projects based on unobservable GP incentives. Efficiency reducing projects are ultimately financed by low quality GPs.

The differences in labor productivity post PE buyout arise in both splits of firms based on LP and GP characteristics. To reconcile these two splits, I document assortative matching between the most underfunded LPs and the lowest quality GPs. This relationship strengthened in the second half of 2000s with the lowest quality GPs 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 PE returns, another sign that more underfunded LPs match to lower quality GPs.[6]

Is it underfunded positions or other characteristics of public pensions correlated with funding ratios, responsible for the match between LPs and GPs? One potential confounder is that the most underfunded LPs might be less skilled in selecting investments, and invest in low quality GPs. In order to cleanly identify the effect of underfunded pensions, I use a novel instrumental variable (IV) for the funding ratio: 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 low quality GPs 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

[6]In equilibrium, matching between the most underfunded public pensions and low quality GPs can be explained by a number of reasons. Low quality GPs 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 LPs and GPs are prevalent (Lerner, Mao, Schoar and Zhang (2022) document preferential access of capital between top LPs and top GPs).

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 gradually worsen the pension's funding ratio.

Using public union density as an instrumental variable for underfunded positions of pensions, I show that more underfunded pensions allocate capital to lower quality GPs, proxied by size. The more unionized pensions earn lower total PE returns. This confirms that the quality effect of assortative matching between more underfunded LPs and low quality GPs is caused by underfunded positions of public pensions and not by LP skill differences. 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. This suggests that capital from the most underfunded public pensions translates into efficiency reducing projects, and capital misallocation.

In terms of the total economic loss, total employment at targets changes by $-\$1.5$ mn. three years after buyout, revenue changes by $-\$670$ bn., and average revenue per employee by $-\$39,850$. Substantial heterogeneity is present across LP type. For firms supported by the most underfunded public pensions, three year cumulative change for average revenue per employee is $-\$54,098$ (-16.2%), while for the other investor firm category it is $\$193,729$ ($+38\%$).

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 low quality GPs which is efficiency reducing. This also suggests importance of transparency between LPs and GPs for public pensions to make better investments. One possible solution is detailed reporting of GP performance at the deal level and by capital source.

Related Literature

The existing research on the real effects of private equity is sparse and inconclusive. The PE industry is opaque, involves many layers of financing from LP to firm via PE fund structures, and data is limited. My paper bridges this gap by unpacking LP-GP relationships, and its ultimate impact on real outcomes, employment, revenue, labor productivity on target firms.

I track 9,300 targets from 1976 to 2019, spanning across industries covering 7% of total U.S. non-farm payroll employment and 11% of total revenue.

My paper contributes to four main strands of literature. First, is the literature on real effects of private equity. Only two papers directly study the effects of PE buyouts on employment and productivity in the aggregate (Davis et al. (2014), Davis et al. (2019)). Davis et al. (2014) studies 3,200 PE buyout until 2003 when PE only started booming. It finds no significant net firm-level changes in employment but increases in TFP for manufacturing targets. Davis et al. (2019) considers PE deals until 2011 to conclude heterogeneous effects of PE on employment based on deal type, i.e., public to private vs. privately held firms. Their paper finds increases in labor productivity post buyout. My paper studies the effects on productivity with a larger and longer sample period, and finds negative productivity effects after 2011. I study both the short run, and long run effects while the prior literature focused on the short run (two years post buyout). Importantly, this is the first study which studies how sources of capital, LPs and GPs, particularly underfunded public pensions play a role in explaining the change in labor productivity effects from the early to the later half of 2000s.

Other 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 such as restaurants (Bernstein and Sheen (2016)), airports (Howell, Jang, Kim and Weisbach (2022)), newspapers (Ewens, Gupta and Howell (2022)), and healthcare (Liu (2021)), thus not giving us representative answers. Kaplan and Strömberg (2009) provides a good overview of the PE industry. This is the first comprehensive study of productivity effects across a wide range of PE buyouts covering 22 industries along with confidential LP-GP relationships in explaining real outcomes at targets.

Second, I contribute to papers which study financial effects of PE (such as, 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, while Leslie and Oyer (2008) finds little evidence of PE-owned firms outperforming public firms in profitability. Amess, Stiebale and Wright (2016) finds a positive impact of PE on firms' patent stock using U.K. data. Bernstein, Lerner and Mezzanotti (2018) discusses if PE contributes to financial fragility during the financial crisis. In sum, what happens to employment, revenue, and productivity patterns post buyout is of key importance and underexplored. Additionally, existing literature has been silent about the investor involved in the PE deal from the target's perspective. My paper bridges that gap by taking an institutional investor (LP) and GP driven perspective of PE deals.

Third, my paper complements the existing literature on relationships between LPs and GPs (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 increased between LP and GP types, and propose that as an explanation for the decrease in productivity at targets. Moreover, the existing PE literature either studies effects of PE funds on firms or investments by LPs into PE funds. This paper studies the full chain of capital flow in private markets from end investors to the end firms.

More broadly, my paper contributes to the institutional investor demand literature. Investors' demand in equity markets (Gompers and Metrick (2001), Bennett, Sias and Starks (2003), Koijen and Yogo (2019), Koijen, Richmond and Yogo (2019)) and corporate bond markets (Koijen and Yogo (2022), Coppola (2022), Siani (2022)) is widely studied. Demand for private assets by institutional investors is understudied, because of the multiple nested fund financing structures and data availability. This is the first paper to connect the demand by investors for private equity funds to the ultimate beneficiaries of those capital flows, the target firms.

Fourth, I contribute to the literature studying pension funds' investment decisions and its incentives (Andonov, Hochberg and Rauh (2018), Andonov, Eichholtz and Kok (2015), 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 real effects of public pensions' investments within private equity. Importantly, I speak to the question of efficiency of capital allocation and projects within PE, driven by public pensions' investments. I introduce a novel instrument, *public unionization rates*, to cleanly identify the effects of *underfunded* positions of pensions. Broadly, I also contribute to the body of work on capital allocation and reach for yield.

On the data front, I develop the first comprehensive database connecting different investor (LP) types, including public pensions, private pensions, insurance companies, sovereign wealth funds, and family offices across countries to PE funds, and ultimately to firms and establishments financed by PE funds. Along with the targets 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.

Section 2 gives an overview of the data and presents institutional details. Section 3 presents productivity effects of PE buyouts in the aggregate. Section 4 shows trends in public pension investments over time, and section 5 documents heterogeneity in real outcomes based on LP and GP types. Sections 6 and 7 discuss matching between LPs and GPs, and identification respectively. Section 8 discusses economic and policy implications. Section 9 concludes.

2 Data and Institutional Background

2.1 Data

I construct a comprehensive dataset of private equity transactions, where I track target firms, corresponding establishments and workers over time. I include details on portfolio holdings in PE funds by institutional investors to study heterogeneous employment, revenue, and labor productivity effects. The sections below describe these in detail.

2.1.1 Private Equity Transactions and Investors

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 among others in PE fund families and PE 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 is the connections between investors (LPs) and PE funds (GPs) within a PE 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 PE funds and firms. I observe the PE fund and family financing the deal, target firm, and the deal date. I also obtain a comprehensive list of attributes of PE funds including their location, vintage, fund family, and industry focus.

I consider private equity funds whose main strategy is a "buyout". Due to differences in structure, I do not consider VC funds that invest in startups. The data on investors, PE funds, and firms spans across all countries, both developed and emerging, from 1979 to 2021, with better coverage post 2000. I merge the supply side and demand side data, to obtain the full chain of capital flow in private markets from end investor (LP) to PE fund (GP) to end recipient (firm). There is no one dataset which covers PE transactions comprehensively. I supplement Preqin with Pitchbook and news outlets to verify deals for accuracy and coverage, and identify the different names of target firms before and after buyout. I manually search individual target websites to ensure accurate location encoding.

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)). Preqin is the only data provider which links the data on LPs, GPs, and PE targets, along with their characteristics. Brown et al. (2015) shows the comparison across different datasets, suggesting unbiasedness of results if any one data source is used.

I complement the private market capital flow data from Preqin with the Public Pension Fund Database (PPD) and 75 FOIA responses from individual state pensions[7] which gives financials and investment allocations of pension funds by asset class over time in the U.S. The PPD tracks 210 public pensions in the U.S., covering 95% of pension fund assets. Since the PPD has coverage starting post 2001, I add financials back to 1983 from FOIA responses. I connect data on public pension financials from PPD and FOIA requests with their investment allocations to PE funds in Preqin through a tedious manual process by pension fund name. I get 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.

2.1.2 Matching with Census micro-data

To track real outcomes at PE targets over time, I merge the PE buyout data with the Census Bureau micro-data. 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.[8] 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.[9] Post merging the buyout deals with SSEL, I use firm-establishment linkages to combine all relevant establishments across years for the matched targets.

Second, I link the merged PE buyout-SSEL data to the Longitudinal Business Database Revenue Enhanced (LBDREV).[10] 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 targets with the LBD allows me to observe granular changes in employment and revenue at firms over time. I get employment, pay, revenue, industry affiliation, along with time consistent linkages between firms and

[7] I thank Anand Systla for FOIA data collection efforts.

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

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

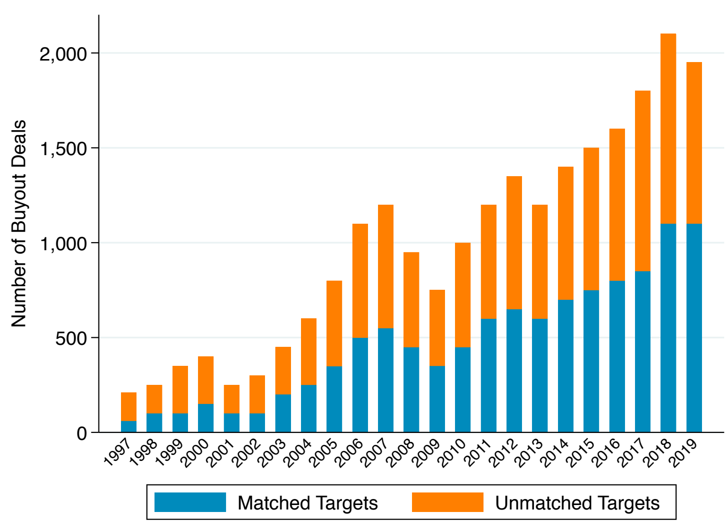
[10] LBDREV is the revenue enhanced and revised version of the original Longitudinal Business Database (LBD). The major improvement of LBDREV over LBD is consistent longitudinal firm and establishment identifiers across time. I will refer to LBDREV as LBD going forward.

establishments. Employment and pay is available from 1976 to 2019, and revenue from 1997 to 2018.

There are multiple hurdles in studying real outcomes at targets post PE buyouts. First, PE 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 years. To encounter these concerns, I study effects on targets around a 5 year window relative to buyout. I merge PE targets with the Census micro-data on multiple dimensions of state, firm name, address.

Figure 1 shows PE targets over years, split by those matched to the Census Bureau micro-data and unmatched. I match 11,850 target firms from 1976 to 2019.[11] Figure 2 shows employment and real revenue in 2020 U.S. dollars at matched targets as a percent of all LBD over time, while figure 17 shows in the buyout year. PE 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 18 shows matched and unmatched firms have similar coverage by industry and state.

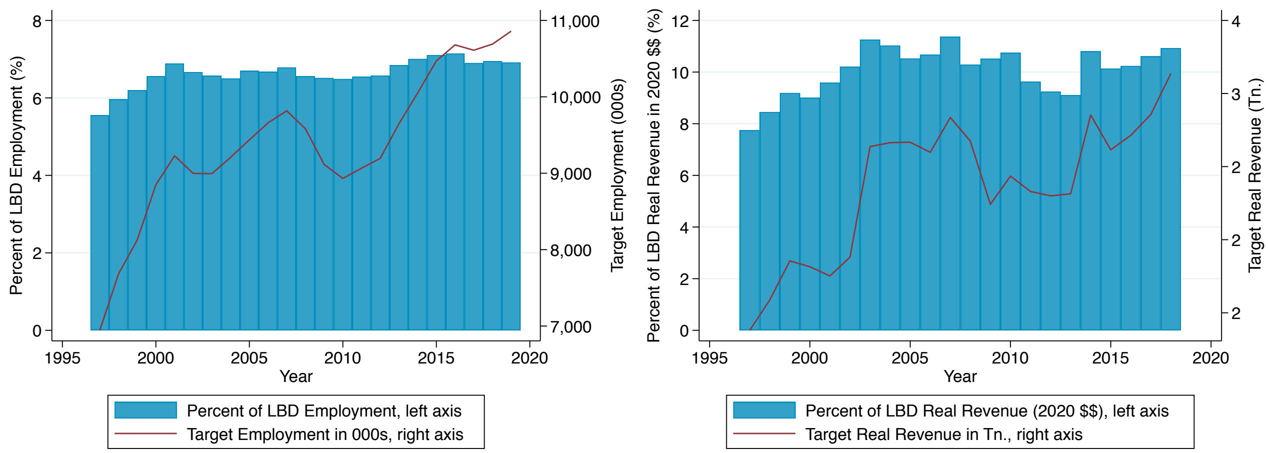
Figure 1. Matched and Unmatched U.S. Target Companies Over Time



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.

[11]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 2. U.S. PE Target Employment and Revenue as a Percentage of Total Non-Farm Payroll Employment and Revenue



(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.

Third, to track productivity of firms over time, I use the Annual Survey of Manufacturers (ASM) and the Census of Manufacturers (CMF) which gives detailed cost measures for manufacturing firms in the sample. Manufacturing targets allow me to study an additional and common productivity measure, total factor productivity.

Fourth, I obtain the worker level earnings measures from the Longitudinal Employer-Household Dynamics (LEHD) for 27 states of the targets.[12] The employer-employee data is provided by the state to the Census Bureau. Worker level earnings are at the firm level. I give a full description of the data and matching in detail in Appendix E and F.

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.

[12] I have access to 27 states for worker level pay. This is generally the number of states the Census makes available to academic researchers.

2.1.4 Final Sample

The final sample has 9,300 targets and 190,000 establishments.[13] Table 1 provides a summary. For 6,700 firms, I am able to construct labor productivity defined as real revenue per employee. My main sample period is 1997 to 2018. Panel A shows PE targets have on average 1,700 employees, $571 mn. revenue in 2020 U.S. dollars, and generate $400,400 revenue per employee.

Out of the 6,700 firms, I match LP identities and characteristics for 5,200 and GP 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 LPs finance a PE deal through 1.4 funds.

In Panel B, I split the targets by investor (LP) category. I identify the dominant LP for a deal based on the maximum amount of capital committed by each LP. 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 GP quality. This measure is proxied by the market value of fund family, including the book and market value of investments. I adapt the fund size based measure of GP quality 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 GP quality 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 31 shows the number of PE funds established has risen from less than 30 in 1990 to over 150 in 2018.

Figure 3 depicts a schematic institutional structure. Capital flows from institutional investors, also called limited partners or "LPs" (left) to firms or "targets" (right). Institutional

[13]This number corresponds to PE targets for which I can construct the control group. More detail in Section 3.1.

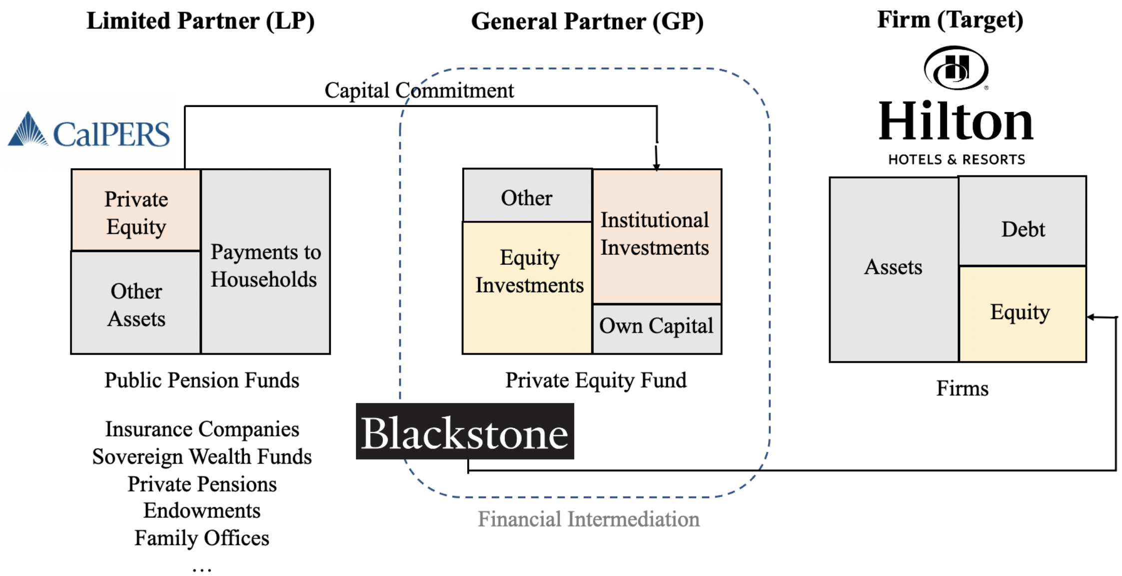
Table 1. Summary Statistics of Private Equity Targets, 1997-2018

	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 GP quality proxied by average market value of assets of GPs financing the target.

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 PE fund family or general partner ("GP", for e.g. Blackstone Group), and its constituent funds (for e.g. Blackstone Capital Partners VI).

Figure 3. 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).

PE funds get majority of their capital, approximately 95% from LPs, while the rest is financed by GPs. The contractual agreement, called the Limited Partnership Agreement (LPA), states contract details between the LPs and GPs including the return and fees. Fees includes a management fee and performance fee, and are negotiated between the LP and GP.

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

The LPs are residual claimants on the net asset value of the fund.

3 Productivity Effects of Private Equity Buyouts

In Section 3.1, I discuss the empirical specification, comparing firm outcomes in PE targets post buyout relative to the control group. Section 3.2 is a post-buyout event study of target firms which forms the baseline for the rest of the paper. Further analysis of manufacturing firms where I study total factor productivity and profit margins directly, including cost and revenue, and tracking employees post buyout is in the Appendix.

3.1 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 PE with similar firms not targeted by PE. 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 PE during their entire history. Specifically, 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. The 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.[14]

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.[15] 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.[16] The number of controls is still greater than the treated, however, this helps me come around the idiosyncracies of selecting a specific firm as a control. I carry out the analysis with employment, real revenue,

[14] Link: `https://www.census.gov/programs-surveys/economic-census/guidance/understanding-naics.html`. I use NAICS code because of better coverage in Revenue Enhanced LBD.

[15] To give an idea, 1500 GB with 32 CPUs and parallel processing is not sufficient to estimate coefficients of these regressions.

[16] First, I consider 10% instead of a fixed number as the number of controls vary significantly in each cell. For example, an IT target firm is expected to have a larger set of controls than a raw material target for buyouts in later half of 2010s. Second, the 10% number is chosen such that different random samples give nearly identical results. I repeat the analysis five times and confirm my results with different random sample draws (Appendix A.5).

revenue per employee, real pay, and pay per employee at the firm level.

To define the main outcome variable of interest, let E_{it} be the employment at firm i in time t. I define $X_{it} = 0.5 \times \left(E_{it-1} + E_{it}\right)$. The Davis, Haltiwanger and Schuh (1996) ("DHS") growth rate is calculated as $g_{it} = \left(E_{it} - E_{it-1}\right)/(X_{it})$. g_{it} captures the one-year growth rate in employment from $t-1$ to t for firm i, and adjusts for entry and exits. Similarly, I calculate growth rates of revenue and total payroll in 2020 U.S. dollars[17], the difference between revenue and employment, and pay and employment growth rates. The first difference is changes in revenue per employee, a measure of labor productivity, and the second difference captures pay per employee changes.

First, I do a non-parametric comparison of growth rates in targets minus control firms five years before and after buyout for deals from 1997 to 2018. Second, I use a difference in difference approach to formalize the results. I present results using the uniform treatment approach from Davis et al. (2014) in Appendix A.1.

Figure 4 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 19 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.[18]

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

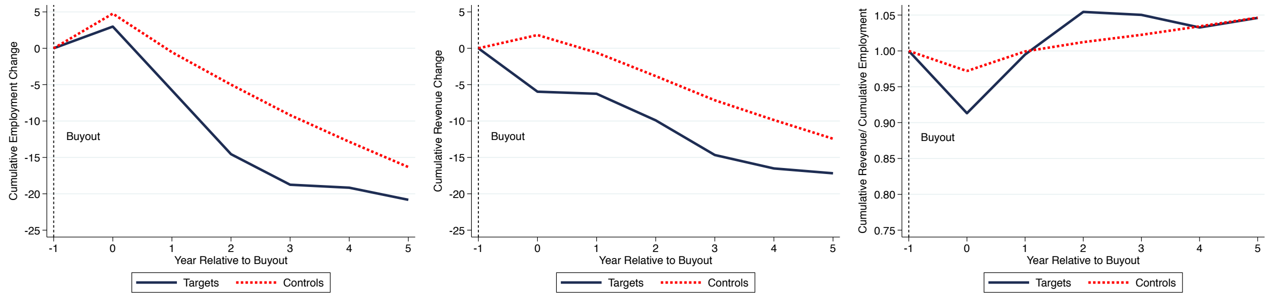
$$y_{it} = \alpha_t + \sum_{j=-5, j\neq -1}^{j=+5} \gamma_j \left(\text{PE}_i \times \text{Buyout Year}_{it_0+j}\right) + \sum_c \theta_c D_{cit} + \lambda_0 \text{LFIRM}_i + \varepsilon_{it} \tag{1}$$

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 PE buyouts on targets relative to control firms in each of the 5 years pre- and post-buyout. As

[17]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).

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

Figure 4. 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

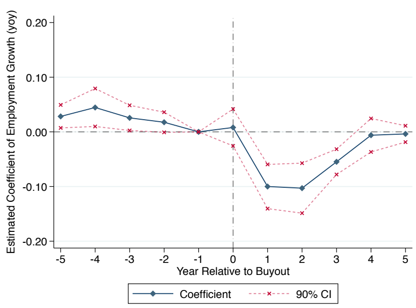
(C) Cum Revenue/ Cum Employment

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.

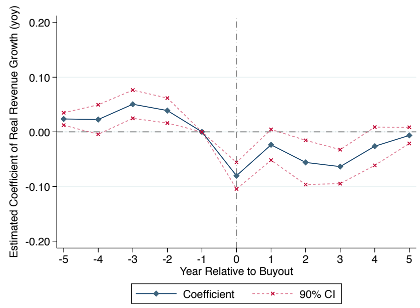
a standard practice, the year before buyout $t_0 - 1$ is the omitted category, and years beyond 5 years pre- and post-buyout are binned with year +/-5 relative to buyout. The regression is saturated with 5,600 dummies D_{cit} capturing industry $\times$ size $\times$ age $\times$ type $\times$ buyout 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 PE. 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 5 tracks the coefficients γ_j 5 years pre- and post-buyout. Panel 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. Further, most of the employment decline happens in the first two years. Second, the parallel trends assumption of the difference in difference specification are satisfied. The control and treated group do not have sigificantly different growth trajectories pre-buyout. This evidence suggests causal effect of PE buyouts on target firms relative to controls. Third, the difference in magnitudes in the non parametric specification, where I do not control for $5,600$ firm characteristic interactions, and the difference in difference specification, which includes these controls, suggests the importance of comparing targets to control firms within a

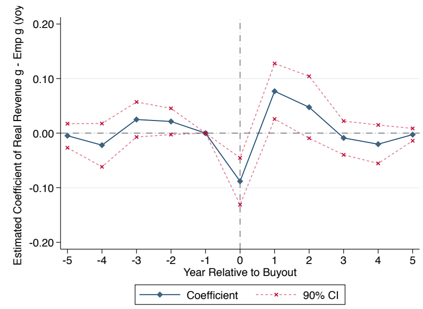
Figure 5. Difference in Difference Estimated Coefficients γ_j Over Time Relative to Buyout Year, PE Deals 1997-2018



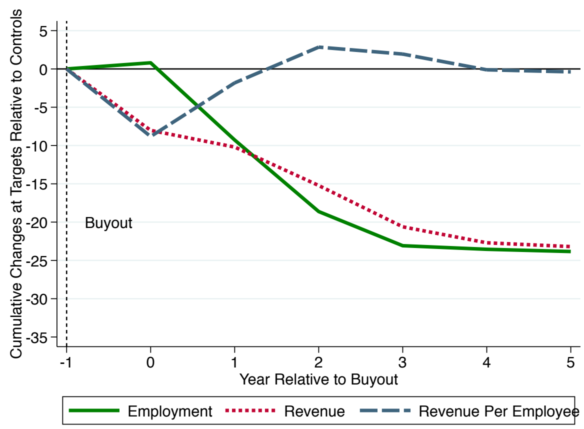
(A) Employment g



(B) Revenue g



(C) Rev g - Emp g



(D) Cumulative Changes

Notes: Figure plots difference in difference coefficients γ_j from equation 1 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.

tightly matched setting. Figure 20 documents effects on firms continuing for at least two years post buyout, and confirms that the decrease in employment is not only due to establishment exits (extensive margin), but also due to layoffs in establishments continuing to exist post buyout (intensive margin).

Table 2 shows the long run effects of PE buyouts on targets relative to control firms, i.e., γ in the difference in difference specification 1 without tracking dynamic effects. Instead of Buyout Year$_{it_0+j}$, I have Post$_{it}$ which takes the value 1 for all years post buyout. I find a -2.7% yearly change in employment, -3.0% in revenue, and -0.3% in labor productivity post buyout.[19] Further, total wages decreases by 2.6%, which implies that total revenue minus

[19]Appendix A.5 (table A.16) confirms the results in other randomly drawn sample of controls. I find a similar magnitudes using employment weights from 3 years pre-buyout (not reported).

wages, measuring operating profits decreases by 0.4%. This shows that while employees are laid off, PE marginally hurts productivity at firms without generating operating profits.

Table 2. Difference in Difference - Long Run Effects of PE Buyouts on Target Relative to Control Firms, PE Deals 1997-2018

Dependent Variable:	Emp g (1)	Pay g (2)	Rev g (3)	Rev g-Emp g (4)
Treatment × Post Buyout	-0.0274^{***}	-0.0263^{***}	-0.0299^{***}	-0.0026
	(0.0083)	(0.0087)	(0.0073)	(0.0078)
Industry × Age × Size × Type × Transaction Year FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Lagged Firm g	Y	Y	Y	Y
Weighted Emp t_0	Y	Y	Y	Y
Observations	25,430,000	25,430,000	25,430,000	25,430,000
Adjusted R^2	0.0372	0.0528	0.0409	0.0080
Dependent Variable Mean	0.0097	0.0139	0.0154	0.0057

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. 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure 22 Panel A shows labor productivity growth rate difference in difference coefficients γ for 17 industries, based on the two-digit NAICS code. Labor productivity effects vary across industries. Construction and professional services are amongst the worst hit industries, facing a -4.5% and -2.8% yearly decline respectively. Most of the other industries show no improvement in productivity, while real estate, educational services, and management shows positive effects. Panel B shows the coefficient by type of firm. PE buyouts decrease productivity of single unit firms by 22% per year, and do not impact multi-unit firms positively. Figure 23 shows these coefficients by firm age and firm size categories. Younger and smaller firms undergo significant productivity declines post buyout. I study employment effects over a longer time period, from 1979 to 2018 in appendix A.3. I find a -29.5% five year change post buyout, larger than the -23.8% change for PE deals in 1997 to 2018.

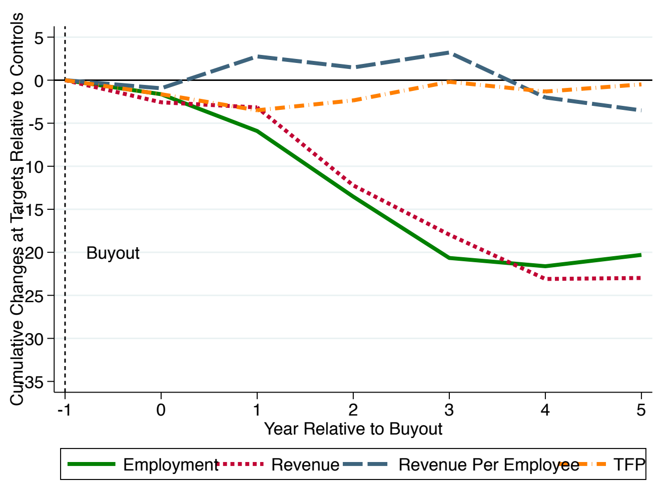
3.1.1 Manufacturing Targets

In the earlier sections, I discussed the effects of PE buyouts on labor productivity. The next question is whether this applies to other measures of productivity, more broadly. Studying 800 manufacturing targets in my sample helps address this question. Using detailed cost metrics from the ASM and the CMF, total factor productivity is 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 written as,

$$\ln \text{TFP}_{eit} = \ln Y_{eit} - \alpha_K \ln K_{eit} - \alpha_L \ln L_{eit} - \alpha_M \ln M_{eit} \tag{2}$$

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. The variables are aggregated to the firm level using employment at establishments as weights. I use the Census computed TFP measure, and confirm results with my own construction. Appendix B.2 shows the results and appendix G.1 details construction of variables.

Figure 6. Cumulative Changes of Outcome Variables for Manufacturing Target Relative to Control Firms Over Time, PE Deals 1997-2018



Notes: The figure cumulates difference in difference estimated coefficients γ_j from specification 1 for manufacturing firms over time relative to buyout year.

Figure 6 shows labor productivity changes by -3.5%, and total factor productivity changes by -0.5% five years post buyout. Employment and revenue changes are similar to the effects on all targets, -20.3% and -23% respectively. These results show the entrance of PE does not positively and significantly improve the productivity of targets.

3.1.2 Subsample Analysis

There is considerable variation in labor productivity effects post buyout at target firms across time periods. Figure 7 panel A, shows a downward shift in labor productivity changes for PE deals in the 2010s. When studying 3,700 PE targets during 1999 to 2011, I find a two year cumulative +7.3% labor productivity change for targets relative to controls post buyout. This is similar to Davis et al. (2019) which finds a two year cumulative +7.5% change for deals executed during this time period. When considering deals from 2011 to 2018, I find a two year cumulative labor productivity change of −5.4%. This shows that while PE had positive effects on targets until 2011, post 2011 has seen PE buyouts contributing negatively to productivity of targets.

When studying the full sample of PE deals from 1997 to 2018, I find a positive two year labor productivity change of +2.8%. Negative labor productivity effects 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. Figure 7 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. For instance, the two year continuing targets from deals in 1997-2018 experience a +3.9% two year cumulative change but a marginal +0.7% five year change. Importantly, both two year and five year productivity changes are lower in 2011-2018 as compared to 1999-2011.

3.2 Event Study around PE Buyout

Next, I focus only on target firms to study post buyout effects.[20] This specification will form the baseline for the LP and GP heterogeneity analysis going forward.

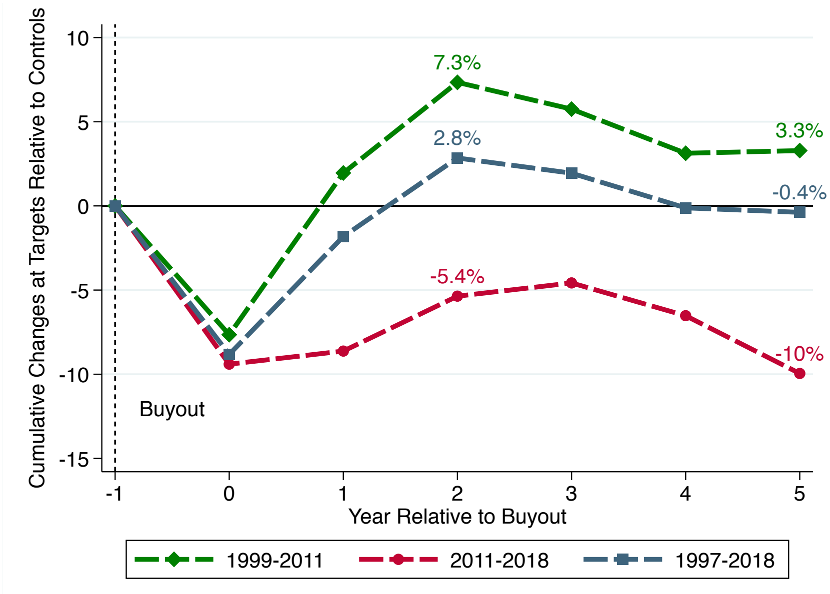
$$y_{it} = \alpha_t + \alpha_0 \text{Post Buyout}_{it} + \gamma \text{LFIRM}_i + \text{Fixed Effects} + \epsilon_{it} \tag{3}$$

Similar to before, y_{it} is the outcome variable in growth rates for firm i at time t. 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. Year fixed effects are included in all specifications.

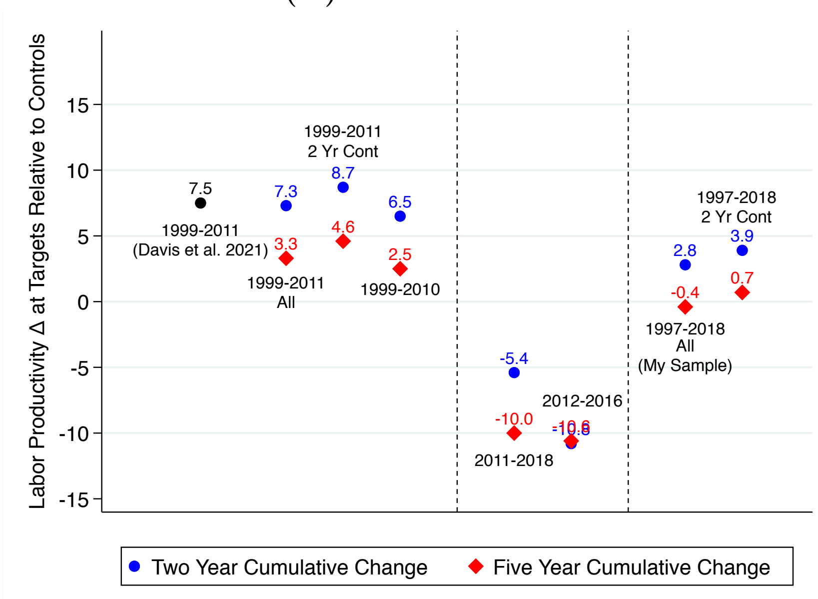
Table 3 shows estimated coefficients α_0 for Equation 3 for year over year growth rates. All columns have year, industry, size, age, and type of unit fixed effects, necessary to account for potential differences across entities and industries. Employment changes by −8.4% per

[20]This specification captures the pre-post "diff" in the difference in difference specification.

Figure 7. 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.

year, revenue by −8.6%, with an insignificant −0.2% change in labor productivity. Figure 24 shows the dynamic estimates five years pre- and post-buyout.[21]

[21] Additional robustness checks (not reported) include specifications with year and industry fixed effects;

Table 3. Event Study Estimated Coefficients of Post Buyout, PE 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 3:

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

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

4 Public Pensions Capital Commitment Over Time

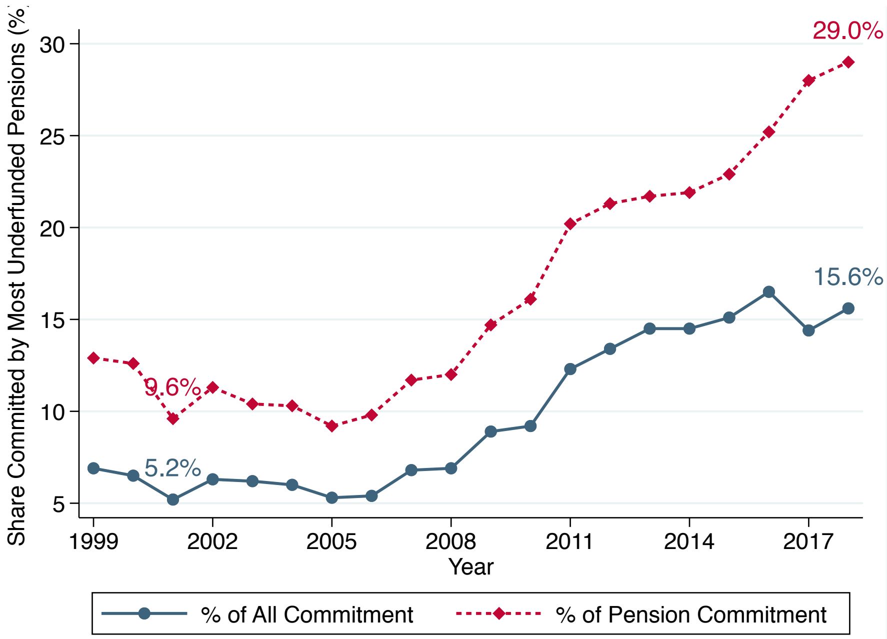
Figure 14 shows allocation to alternatives by public pensions have increased from 8% in 2001 to 27% in 2020. Further, the share of capital committed by the most underfunded public pensions has increased. I combine the pension assets and liabilities with the LP commitment amounts, and split pension funds into terciles based on their underfunded ratios at the time of capital commitment.

Figure 8 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.

In the time series, the rising importance of PE investments by the most underfunded public pension funds coincides with the deteriorating performance of said PE investments shown in Section 3.1.2. Specifically, substantial increases are seen post 2010, the period after

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 × year, firm size, age, and type fixed effects. Results remain unchanged.

Figure 8. Capital Commitment by 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 PE buyouts matched to Census micro-data. Data are sourced from Preqin, Public Pensions Database, and FOIA requests.

which PE buyouts decreased labor productivity at targets. This suggests the importance of public pension capital in private equity as a mechanism of understanding decreases in labor productivity at targets.

LPs commit capital to GPs, and the management of targets is controlled by the GPs. The relationship between LPs and GPs is key to understanding how investors' capital can ultimately impact real outcomes. Rest of the paper exploits cross-sectional variation to show that the source of capital has differential effects on targets, discusses the mechanism behind this, and presents an IV estimation strategy to bolster the case for a causal interpretation.

5 Source of Capital Heterogeneity

What explains the decrease in labor productivity at firms after PE funds buy the target? Targets are bought by commingled funds, where capital by multiple investors is pooled together. To explain productivity differences at the firm level, I directly look at the contributors of capital, LPs and GPs. Section C.1 follows an approach similar to Abowd, Kramarz and Margolis (1999), and adds LP and GP identity interactions with Post Buyout$_{it}$ in specification 3. I show that total R squared increases from 1.6% to 10.9% with LP interactions, thus lending support that the source of capital plays a significant role in studying effects on target firms post buyout.

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 PE funds in 38.1% of the cases. This is the most sensitive information between the LP and the GP. 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 LPs are involved in financing a deal though commingled PE funds. 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 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.

On the main factors distinguishing public pension funds as compared to other investors is their underfunded positions. To identify firms supported by the most underfunded pensions, I calculated funded ratios at the firm level i, weighted by the capital committed by the individual pension fund p to firm i via PE fund j, representing LP presence in the deal,

$$\phi_i = \frac{\sum_{pji} w_{pji} \cdot \text{Underfunded Ratio}_{p,p\in ji}}{\sum_{pji} w_{pji}} \tag{4}$$

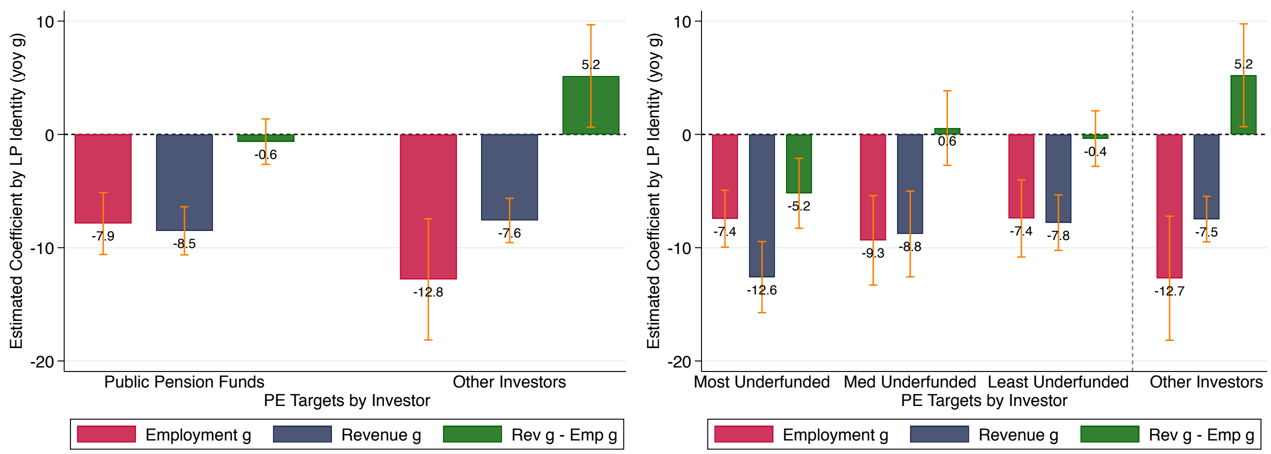
I split ϕ_i into terciles to estimate the following specification.

$$y_{it} = \alpha_t + \alpha_0 \text{Post}_{it} + \sum_{r=1}^{3} \beta^r \left(\text{Post}_{it} \times \mathbb{I}_i^{UF^r}\right) + \gamma \text{LFIRM}_i + \text{Fixed Effects} + \epsilon_{it} \tag{5}$$

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 rule out the concern that different LPs and GPs are selecting into different types of firms. Controlling for pre-buyout growth trends alleviates the concern of selecting into growth targets.

Figure 9 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). Panel B splits the public pension supported firms into terciles based on underfunded ratio of pensions. Deals financed by other investors experience a 5.2% increase in labor productivity per year, whereas those financed by public pensions face a -0.6% insignificant yearly productivity decline. This points to specialness of public pensions as LPs in financing firms. Within public pension supported firms, firms supported by the most underfunded pensions (1,200 firms) face a -5.2% productivity decline on a yearly basis.

Figure 9. Estimates of Post Buyout × Investor Type, PE Deals 1997-2018



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

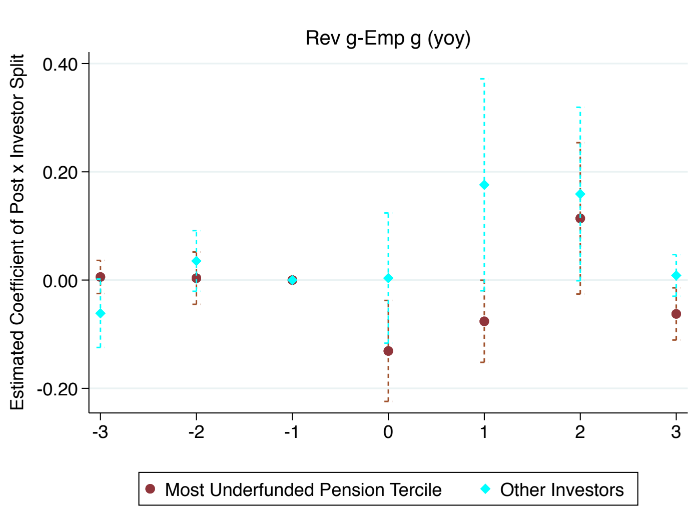
Notes: Panel A plots coefficients for equation 5 with two categories: other investors and public pension funds supported firms. Panel B plots coefficients from four categories in equation 5: other investors, most underfunded, medium underfunded, and least underfunded public pension supported firms. Bars represent 90% confidence intervals.

Tables 9 and 10 show the incremental differences are large and significant. Firms supported by the most underfunded pensions experience a -10.4% productivity decline 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 by investor characteristics in target firms, which is not visible in the aggregate effects.

This evidence holds on different splits of the data. Figure C.46 splits pensions into quartiles, and finds similar results. When looking at only public pensions, I find similar effects: the least funded public pension supported firms face a -5.5% to -5.3% decrease in labor productivity per year.[22] To account for macroeconomic conditions, I residualize underfunded ratios with local region fixed effects and 10 year interest rates, and find similar results (figure C.45).

Figure 10 shows estimates of yearly labor productivity growth rates pre and post buyout for the most underfunded pension supported firms, and firms supported by other investors. First, firms supported by other investors experience positive productivity changes consistently post buyout, whereas the most underfunded pension supported firms face productivity losses in most of the years following buyout. Second, the parallel pre-trends hold for both categories of firms. This means that firms in the two categories were not significantly different from each other. This suggests that financing from different investors causes firms to generate varying productivity gains (losses) depending on the investor type. However, I cannot rule out selection by LPs and GPs for firms based on unobservables such as preferences, or pressure from management, which is not captured by observable firm and investor characteristics.

Figure 10. 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 $\beta^r_j,\ j = -3, \cdots, 3$ for the dynamic version of equation 5 for three years before and after buyout for the most underfunded and other investor category of firms. Connected lines represent 90% confidence intervals.

LPs provide capital to GPs who ultimately invest in firms. GPs are the active managers directly engaging with operations of targets. To uncover variation in GP charactersitics in explaining outcomes at targets, I construct a measure of quality based on the mutual fund literature. Berk and van Binsbergen (2015) shows that managerial skill is reflected in the cross-sectional distribution of fund size and assets under management (AUM). I will adapt this to PE funds, and interpret it more broadly as a measure of GP *quality*. Smaller GPs

[22] I do not identify a dominant investor for each deal in this split, but directly take the weighted average of underfunded ratios across public pensions, using capital commitment as weights (figure C.44, table 11).

have smaller assets, less number of PE funds, and less connections – all measures which might ultimately impact performance of GPs. This is a useful measure, especially for non-traded fund families.

I use two proxies for GP quality: (1) market based measure, which is the sum of book value of capital committed by LPs to GPs, additional market value of GP investments, and capital yet to be called ("dry powder"), covering all asset classes[23], and (2) book value measure, which is the sum of total size of existing PE funds within the family for each year. I use the year of inception and lifespan of the fund to determine years of existence for each PE fund. When I do not observe the lifespan, I take the median value of 10 years (similar to Kaplan and Strömberg (2009)). The second measure allows me to track fund family size over time, and consider the presence of a GP in the year of deal. Higher private equity book value assets represents bigger scale and better quality within the PE industry.

To capture differences on target outcomes based on fund family quality, I aggregate GP quality measures at the firm level. I weight fund family characteristics by the number of funds within a family involved in a deal. Rankings across GPs are persistent over time and across measures.

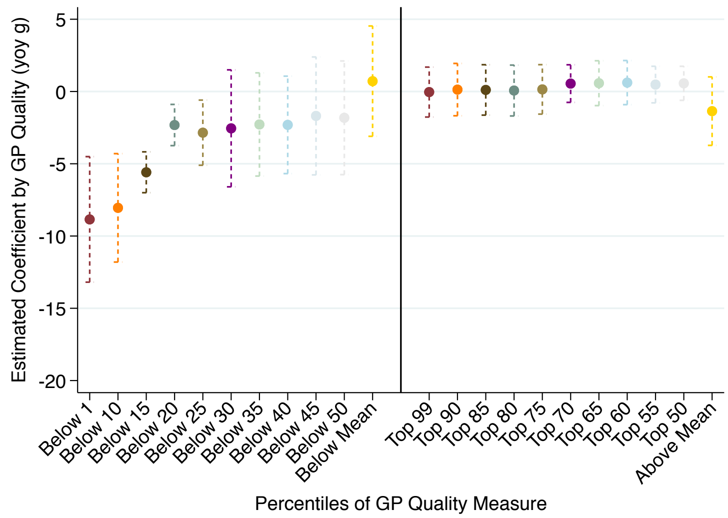
I estimate specification 5 with varying splits of firms based on GP quality distribution. Figure 11 shows firms supported by the lowest quality GPs experience greatest decreases in productivity. For instance, firms supported by the bottom 20th percentile experience -2.3% year over year labor productivity 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. Figure 25 shows that while most of the employment effects are similar across GP distribution (panel A), the difference in revenue generation post buyout activity (panel B) results in differences in labor productivity.

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 GP quality supporting the deal. Inclusion of granular controls allow me to get closest to comparing similar firms undergoing a buyout. To a certain extent, the evidence suggests causality, i.e., funds causing decreases in labor productivity. However, there can still be a possibility of GPs having preferences for certain types of firms, which are unobservable and not captured by the granular controls. Hence, labor productivity effects on firms post buyout based on different

[23]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.

GP qualities, can capture both causality and selection into investment projects.

Figure 11. Labor Productivity g Estimates of Post Buyout × GP Quality Percentile, PE Deals 1997-2018



Notes: The figure shows estimates from equation 13, where GP_j is substituted with different size percentile splits of targets. Interaction term of $(\text{Post Buyout} \times \text{LP}_k)$ is omitted. Each color shows estimates from a different regression. Bars represent 90% confidence intervals.

LPs are the ultimate providers of capital to target firms. Given the nature of their contract with GPs, once the capital is committed LPs do not have an active role in determining capital allocations in deals. One would hypothesize that the identity of the investor should not affect the firm outcomes. Studying pension funds, the biggest investor in private equity, I find that this is not the case.

6 Mechanism and Discussion

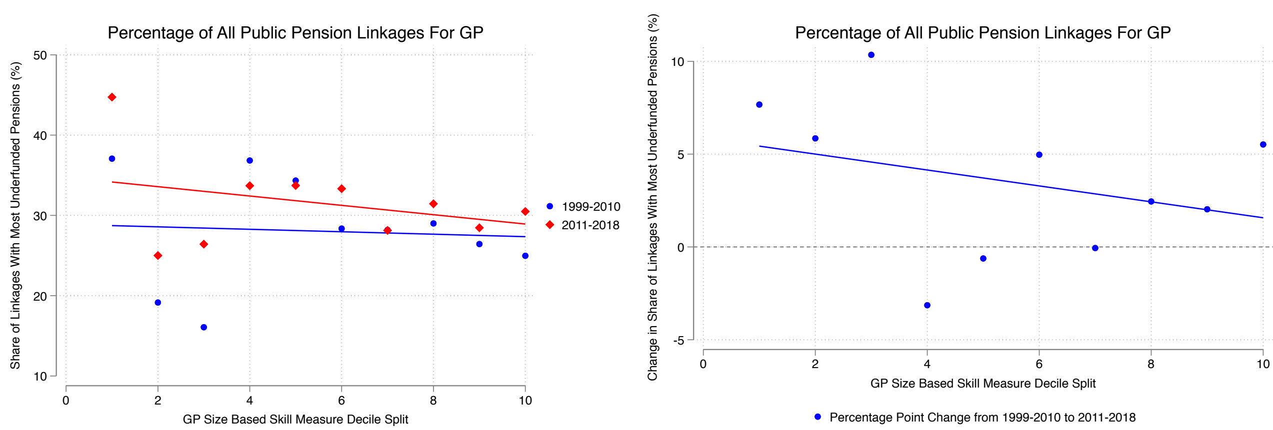
6.1 Matching Between LPs and GPs

Having shown that firms financed by the most underfunded public pensions and lowest quality GPs, both experience a decrease in labor productivity, suggests a connection between the two agents. In this section, I document assortative matching between LPs and GPs to explain differences in productivity by investor heterogeneity.

I use the market based measure of GP quality to split GPs into deciles. LPs maintain the same split of most underfunded pensions, medium underfunded, least underfunded, and other investors. I focus on public pensions to highlight differences within pensions in their allocation to different GPs. I consider underfunded ratios of pensions at the time of capital commitment to a PE 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 PE fund. This is reasonable as a PE fund receives most of its capital commitments when the fund is set up.[24] Consequently, I split LPs based on their underfunded ratios for each year separately.

I count investment linkages between LPs and GPs based on their characteristics. Investment linkages represents the number of times an LP invests in a fund family within a given time period. Figure 12 shows percent of investment linkages between the most underfunded pensions and GPs in the two time periods: the 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 lowest quality GP 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 PE investments are long-term, sticky, and relationship based.

Figure 12. Percent of Investment Linkages Between Most Underfunded Pensions and GPs Across Time



Notes: This figure counts connections of invesment links between the most underfunded public pensions and GPs for two time periods: (1) 1999-2010 and (2) 2011-2018. The year of commitment is the vintage year of the PE 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 GP quality measure is negative in 2011 to 2018, the second half of the sample (red line). This shows that lower quality GPs 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

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

for lower quality GPs.[25] The higher quality and big sized GPs such as Blackstone Group, Kohlberg Kravis Roberts & Co. (KKR), and Goldman Sachs Alternatives (AIMS) Group have connections with all types of investors. The lower skilled GPs 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 existence of assortative matching between the most underfunded public pensions and the least skilled GPs.

Formally, I regress the GP size based quality measure on underfunded positions of public pensions in the year of capital commitment.

$$y_{pst|p\in j} = \gamma_t + \beta \cdot \text{Underfunded Ratio}_{pst} + \text{Controls} + \epsilon_{pst} \tag{6}$$

where, p is public pension, s is state, j is GP, and t is year of capital commitment. y is total size (in logarithmic terms) of the GP in year t, which is the sum of size of all its component funds existing in that year.[26] For each pension, I take the average size across GPs of pension fund investments for each year, to aggregate to a pension fund-capital commitment year level for estimating equation 6.

I control for public pension characteristics: LP 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 GPs rather than lower quality GPs, I control for multiple GP 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 to allow for matching across LPs and GPs.

Column 4 of table 4 shows estimates for the most saturated specification of pension fund and GP controls. More underfunded pensions allocate capital to lower quality GPs within their PE allocations. Coefficient for underfunded ratio is -0.62 ($t = -3.17$), and is statistically significant at 1% level. The effect 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, average GP size based quality measure is $\$7,274$ mn., and 0.11 log

[25] The result is consistent across GP splits. As a robustness, I split GPs into 20 cateogories and find similar evidence of steepening of the curve.

[26] Details of the measure defined in Section D.1.

Table 4. More Underfunded Pensions Match with Lower Quality GPs, 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

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

point change corresponds to a -10.3% change.[27]. The 10.3% decrease in size of the PE 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 lowest quality GP from the most underfunded pensions (figure 12). Similarity of magnitudes across the two GP quality measures lends support for comparability of the quality metrics. Additionally, studying changes in capital flow from both the GP's and LP's perspective confirms the matching story.

6.2 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 category being 4.4%. To cover for underfunded positions, it is plausible that the severely underfunded pensions ex-ante expect higher returns from PE investments. However, I find ex-post that the most underfunded pensions realize lower PE returns.

I estimate specfication 6 with y_{pst} being total realized PE returns for pension fund p in time t. I now include pension fund fixed effects. I have pension fund characteristic controls as before,

[27] 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.

but not for GP as these regressions are solely at the pension fund-year level. The regressions estimate the effect of pensions' underfunded positions on its total PE realized returns. Table 5 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 underfunded 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). This suggests that more underfunded public pensions are allocating capital to worse performing investments, a *quality* effect.

Table 5. Correlation Between Public Pensions Underfunded Positions and PE 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

Standard errors in parentheses

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

The more underfunded public pensions match to lower quality GPs which are underperforming. Lower total PE returns earned by the more underfunded pensions provides circumstantial evidence in support of this story. Underperformance of lower quality GPs is visible in the significant decreases in productivity at target firms. This provides evidence that the *desperate* capital need of severely underfunded public pensions which makes them target specific fund families, leads to an inefficient capital allocation in the economy.

7 Identifying Desperate Capital Using Public Unions

7.1 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 26). To cleanly identify the effects of *underfunded positions* of pensions, i.e., desperation, in driving more underfunded pensions to allocate capital to low quality GPs, I want to rule out unobservable characteristics of LPs which might be correlated with underfunded positions and GP quality. One possible confounder is LP skill. Underfunded pensions might also be low skilled which might lead them to mismanage capital resulting in higher underfunded ratios, and higher allocation to low quality GPs. 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 GPs, 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,

$$\text{Union Density } (\%)_{st} = \frac{\text{Number of members}_{st}}{\text{Number of Government Employees}_{st}} \tag{7}$$

There is a wide cross-sectional variation in public unionization rates across states. Figure 28 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.[28] Freeman (1983) shows unions increase pension coverage. Figure 29 shows evidence of a

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

+17.3% significant correlation between underfunded public pensions and one year lagged public union density for 2011 to 2018.[29]

Second, the exogeneity condition should hold, i.e., public unionization rates affects investments by pensions to specific GPs, and returns within PE only through pension 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.

7.2 Empirical Methodology and Results

Formally, the first and second stage of the empirical specification are shown in equations 8 and 9 respectively.

$$\text{Underfunded Ratio}_{pst} = \alpha_t + \beta \cdot \text{Union Density } (\%)_{st-1} + \text{Controls} + \epsilon_{pst} \tag{8}$$

$$y_{pst|p \in j} = \gamma_t + \beta_{IV} \cdot \widehat{\text{Underfunded}}\ \text{Ratio}_{pst} + \text{Controls} + \epsilon_{pst} \tag{9}$$

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

Table 6 reproduces the OLS from Column (4) in tables 4 and 5, and presents the first and second stage IV results. The first three columns correspond to *GP Quality*, and the last three show results for *Realized PE Returns*. The first stage coefficient of interest is β, and expected to be positive. For GP Quality for instance, 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

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

Table 6. Instrumental Variable Results for GP Quality and Realized PE Returns

	GP Quality			Realized PE 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 8, 6, and 9. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 GP size and PE 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 results, i.e., desparate capital, and not other LP characteristics such as low LP skill which might be correlated with the funded ratio. I get similar results in economic and statistical significance when studying public pensions and GPs supporting firms which are matched to the Census data.

To futher substantiate the cause for underfunded positions, I estimate specification 5 by splitting targets into terciles of state public union density of the corresponding public pensions supporting the target. Column (1) of table 7 reproduces estimates from equation 5, 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%.

Table 7. Post Buyout Labor Productivity Effects by Investor Split Using Union Density

Investor Split	Rev g-Emp g Underfunded Ratio (1)	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 5. 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 10 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

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 underfunded positions of pensions, and not other public pension characteristics, which is *causing* pensions to invest in low quality GPs, decreases labor productivity at targets, and realizes lower PE returns.

8 Economic and Policy Implications

8.1 Economic Implications

An important question is what is the magnitude of economic loss or gain from private equity post buyout. More importantly, how do the gains or losses vary by investor type. In this section, I look at changes for employment, and changes in dollar value for revenue, and revenue per employee based on the estimates produced in previous sections.

Table 8 shows the economic loss in target firms relative to the control firms in the aggregate. Magnitudes are based on PE 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. Control firms marginally increased employment (+0.3%), increased revenue (+2.6%), and increased labor productivity (+2.3%).

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 10 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.

Table 8. Economic Loss and Gain by Investor Between Year −1 and +3 Relative To Buyout

		Employment (1) (000s)	Employment (2) (%)	Revenue (3) ($$ Bn.)	Revenue (4) (%)	Revenue Per Employee (5) ($$)	Revenue Per Employee (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 5. Revenue is deflated by the U.S. GDP Price Deflator Series, and is expressed in 2020 U.S. dollars.

8.2 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 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 private equity. However, my paper shows that ex-post more underfunded public pensions invest in efficiency reducing projects. 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 allocations also don't increase efficiency. The most underfunded pensions ex-post realize lower PE returns.

The PE industry is opaque and transaction based. Having shown that private equity is not adding value in terms of labor productivity, and yet the fact that their investments generate lumpsum returns to the GPs lends concern towards the companies targeted by PE. Moreover, public pension investments in private equity are not regulated. My paper provides support for increase in transparency between LPs and GPs. Further, a cap on public pension investments in PE would be a relevant policy consideration.

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. Thus, underfunded positions of public pensions have broader implications for municipal and state finances, and potential stability of retirement systems.

I believe the phenomenon of *desperate capital* and selecting into low quality funds, 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. Further, one can expand this notion to focus on other investors and characteristics investing in different asset classes.

9 Conclusion

This paper studies the real effects of private equity buyouts, on firm employment, revenue, and labor productivity. Using a sample of 6,700 buyouts from 1997 to 2018, I show that while private equity led to substantial increases in labor productivity at targets relative to control firms in the first half of 2000s, the second half has seen substantial decreases in labor productivity. The inference is based on an extremely tight matched sample of control firms. The decrease in labor productivity at targets post buyout coincides with an increase in capital from the most underfunded public pensions to private equity. Capital from the most underfunded pensions as a percentage of all capital commitments increased from 5.2% in 2001 to 15.6% in 2018.

Using a novel data of LP and GP linkages with the target and capital commitment amounts, I 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 low quality GPs show decreases in productivity.

I show that the most underfunded public pensions match with low quality GPs. Moreover, the most underfunded pensions realize lower PE returns, which suggests underperformance of GPs passes to the LPs. To strengthen causality from underfunded positions, I use a novel instrument of variation in public unionization rates across state-year, and I confirm the selection from the LP to the GP is driven by underfunded positions. These results support the notion of *desperate capital* – which is that desperate public pensions with highly underfunded positions select into low quality GPs, ultimately resulting in productivity losses at targets. My paper thus shows capital misallocation via private markets, and it has important policy implications for public pension investments in PE, and for potential stability of retirement systems.

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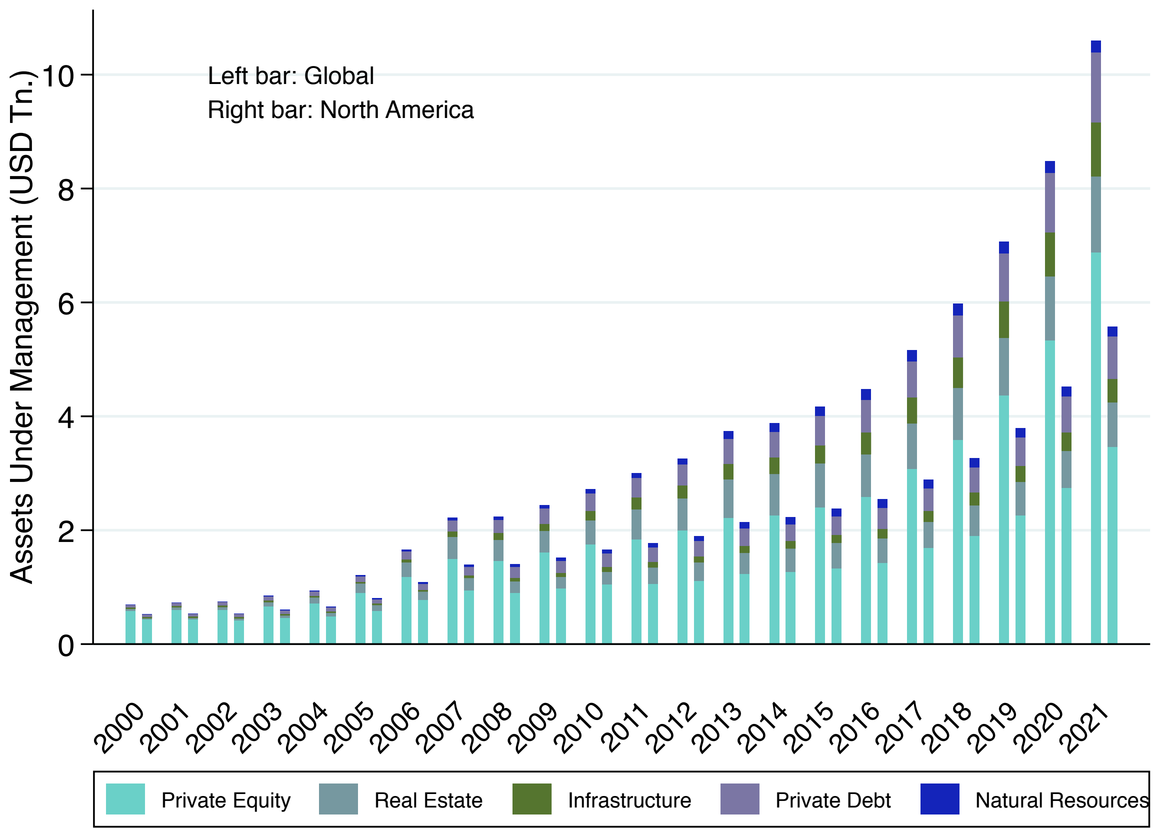
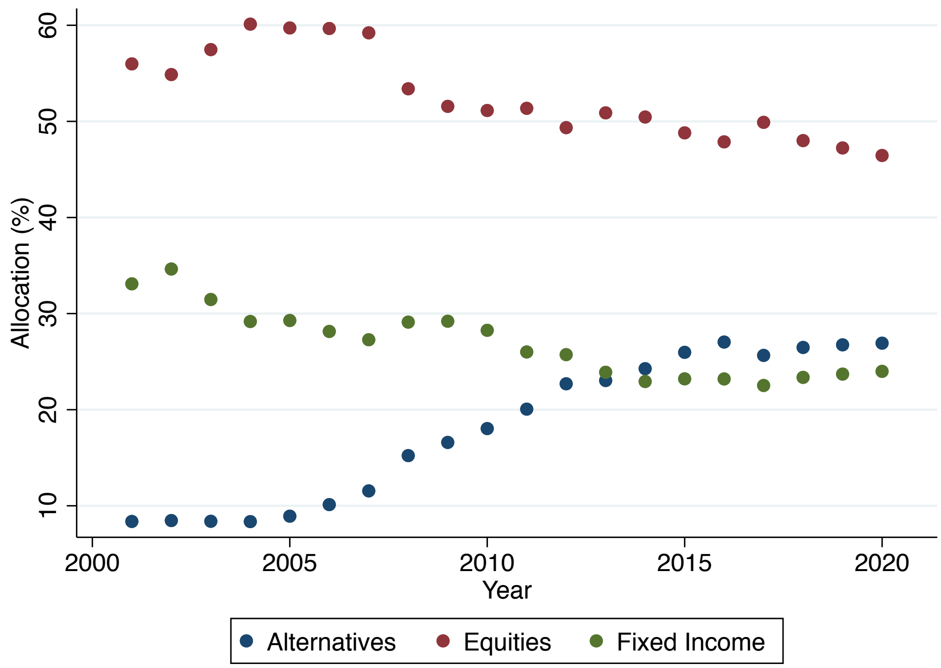
A Additional Figures and Tables

Figure 13. Private Capital Markets Over Time

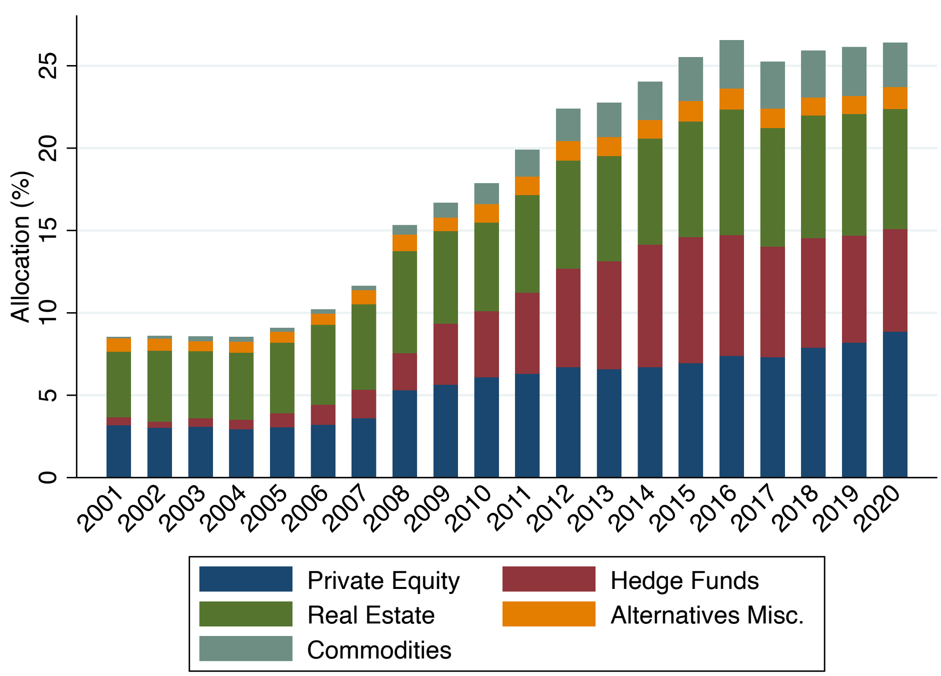


Notes: This figure shows growth of private capital markets from 2000 to 2021. Private capital, also referred to as "alternative assets" consists of private equity (PE), real estate (RE), infrastructure (INF), private debt (PD), and natural resources (NR). The bars represent total assets under management (AUM) in USD Tn. To avoid double counting of available capital and unrealized value, fund of funds and secondaries, i.e., PE transactions in the secondary market are excluded from this plot. The left bars correspond to global AUM, right bars represent AUM in North America. Data are sourced from Preqin.

Figure 14. Portfolio Allocation of U.S. Public Pensions Over Time



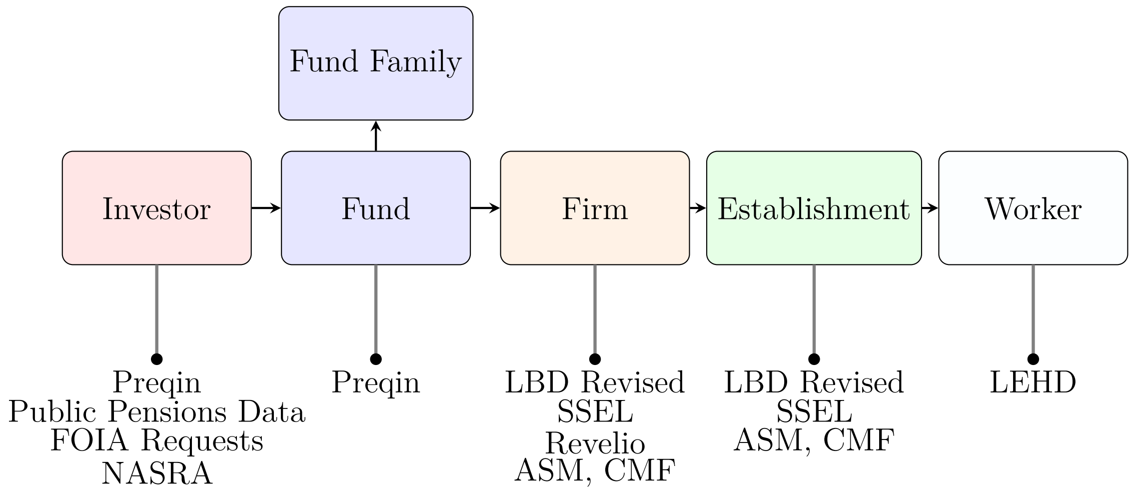
(A) Across asset classes



(B) Within alternative assets

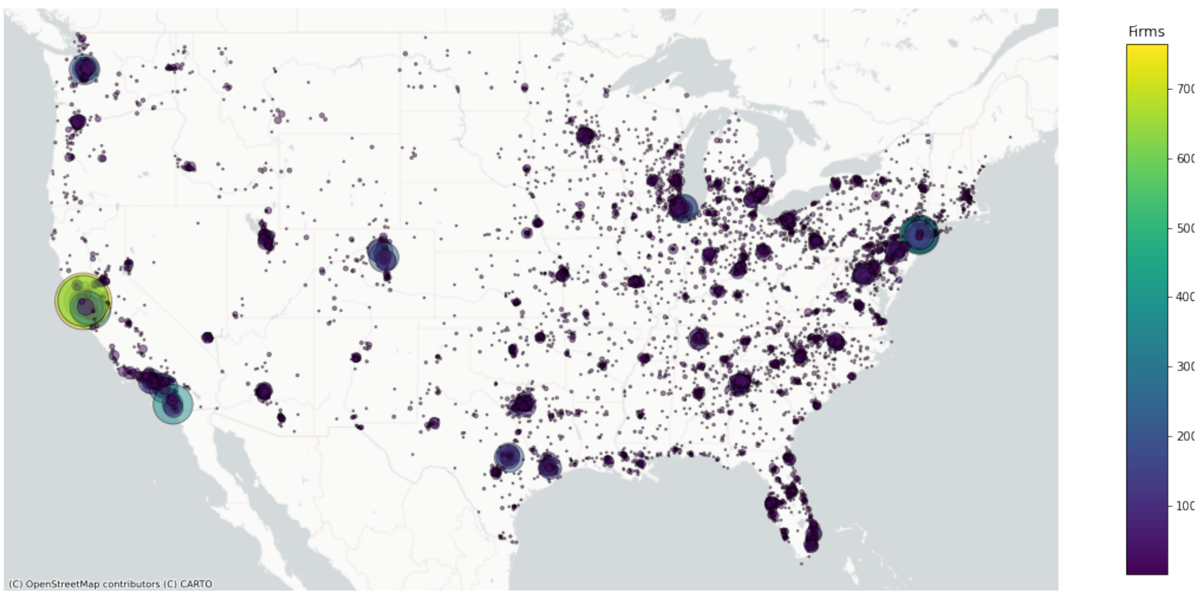
Notes: The y axis represents portfolio allocation of assets as a percentage of total assets. Panel A shows asset allocation of U.S. public pensions *across* asset classes over time. Panel B focuses on *within* the alternative asset class. Data are sourced from Public Plans Data (link: https://publicplansdata.org/).

Figure 15. Visualization of Data and its Sources



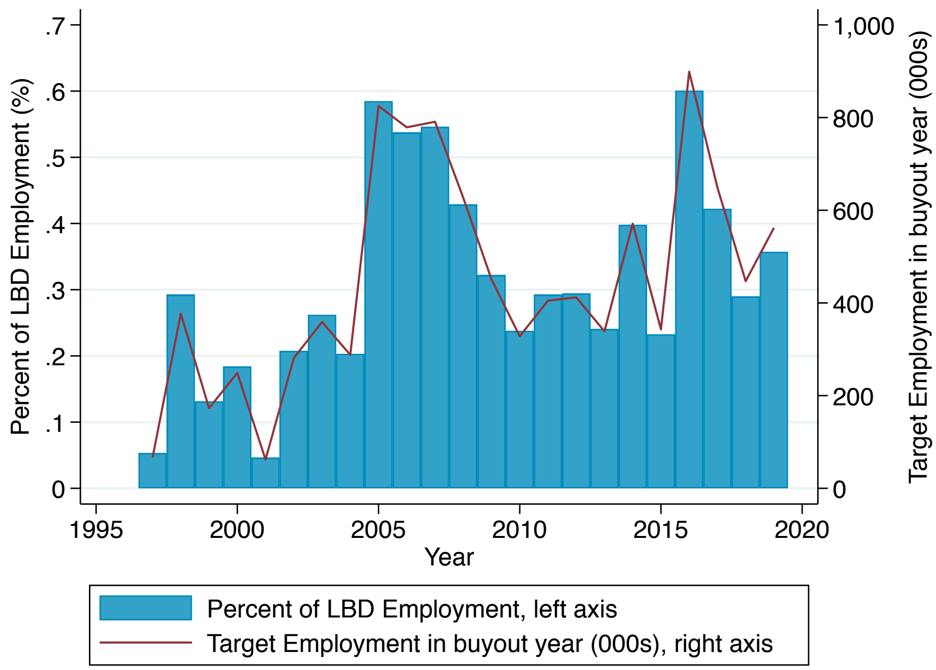
Notes: The figure draws connection between the data and its sources. LBD – Longitudinal Business Database. SSEL – Standard Statistical Establishment Listing. ASM – Annual Survey of Manufactures. CMF – Census of Manufactures. LEHD – Longitudinal Employer-Household Dynamics. FOIA – Freedom of Information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

Figure 16. U.S. Firms Receiving Capital From Private Equity

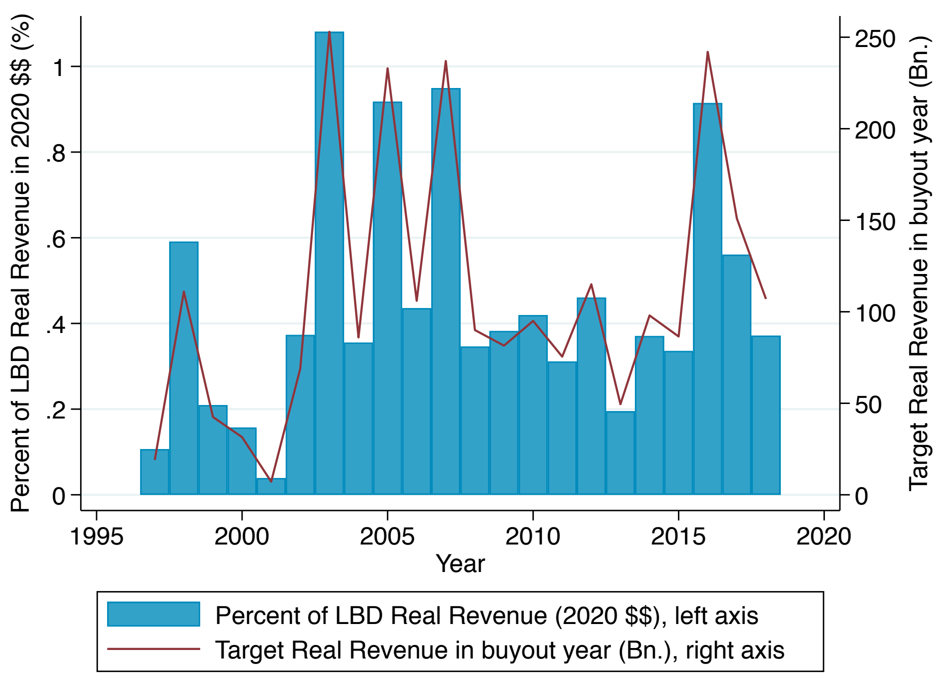


Notes: The figure shows geographic dispersion of companies which have received capital from private equity at least once since 1976. The lighter colors correspond to more concentration of firms receiving PE capital in the area, while the darker colors represent smaller number of firms receiving PE capital. Data are sourced from Preqin.

Figure 17. U.S. PE Target Employment (Revenue) as a Percentage of Total Non-Farm Payroll Employment (Revenue) in Buyout Year



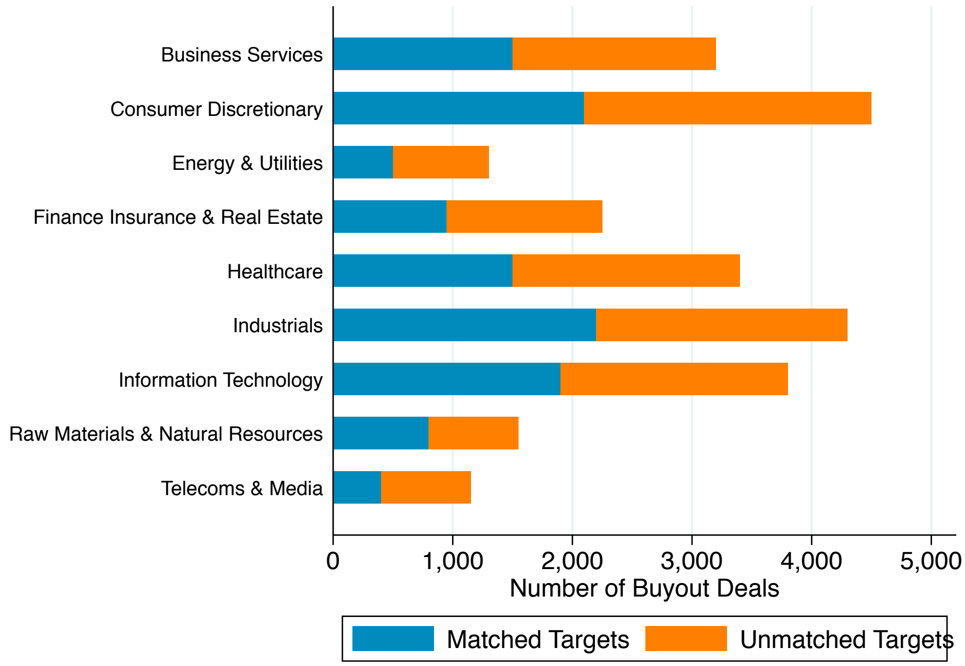
(A) Employment



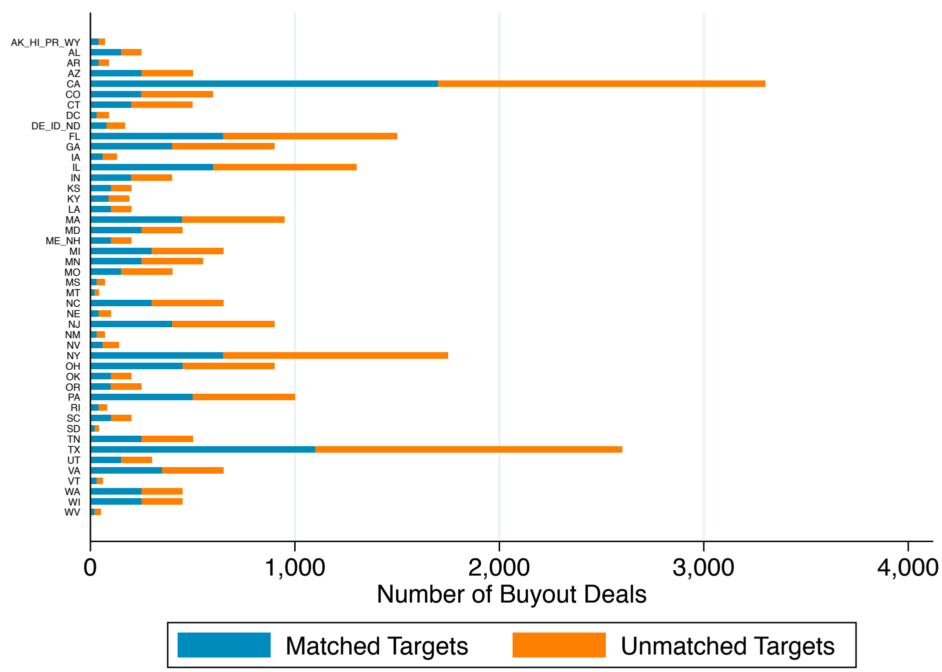
(B) Revenue

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.

Figure 18. Matched and Unmatched Targets by Industry and State



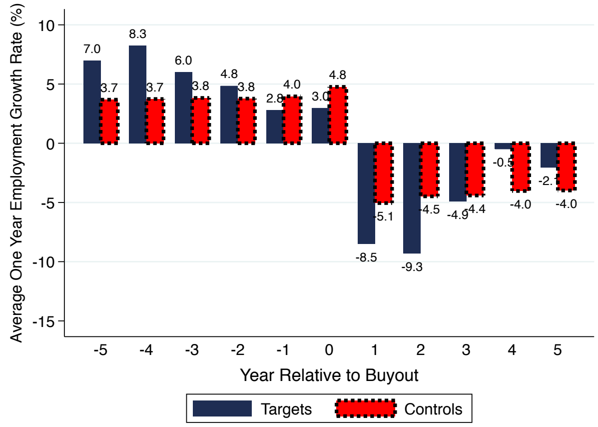
(A) By Target Industry



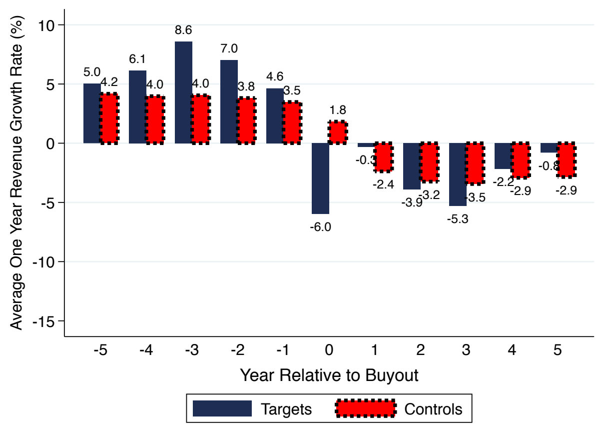
(B) By Target State

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.

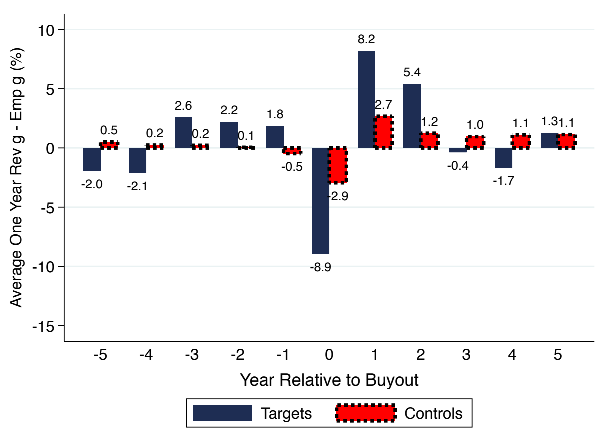
Figure 19. Non Parametric: Changes in Employment, Revenue, and Labor Productivity at U.S. Target and Control Firms Pre and Post Buyout, PE Deals 1997-2018



(A) Employment g (yoy)



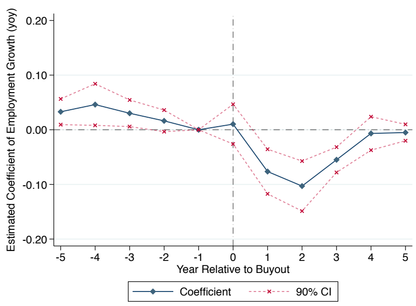
(B) Revenue g (yoy)



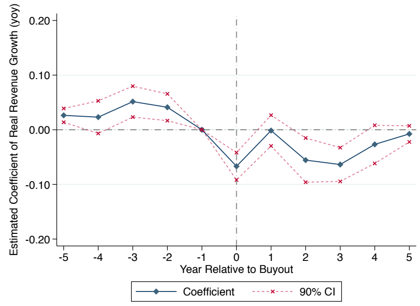
(C) Rev g (yoy) - Emp g (yoy)

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.

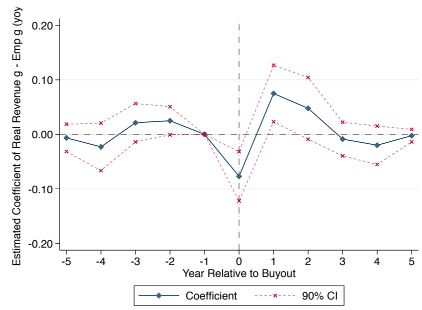
Figure 20. Difference in Difference Estimated Coefficients γ_j for Two Year Continuing Firms, PE Deals 1997-2018



(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	-0.0261^{***}	-0.0266^{***}	-0.0005
	(0.0084)	(0.0073)	(0.0079)
Industry × Age × Size × Type × Transaction Year FE	Y	Y	Y
Year FE	Y	Y	Y
Lagged Firm g	Y	Y	Y
Weighted Emp t_0	Y	Y	Y
Observations	$14,830,000$	$14,830,000$	$14,830,000$
Adjusted R^2	0.0394	0.0405	0.0092
Dependent Variable Mean	0.0088	0.0155	0.0067

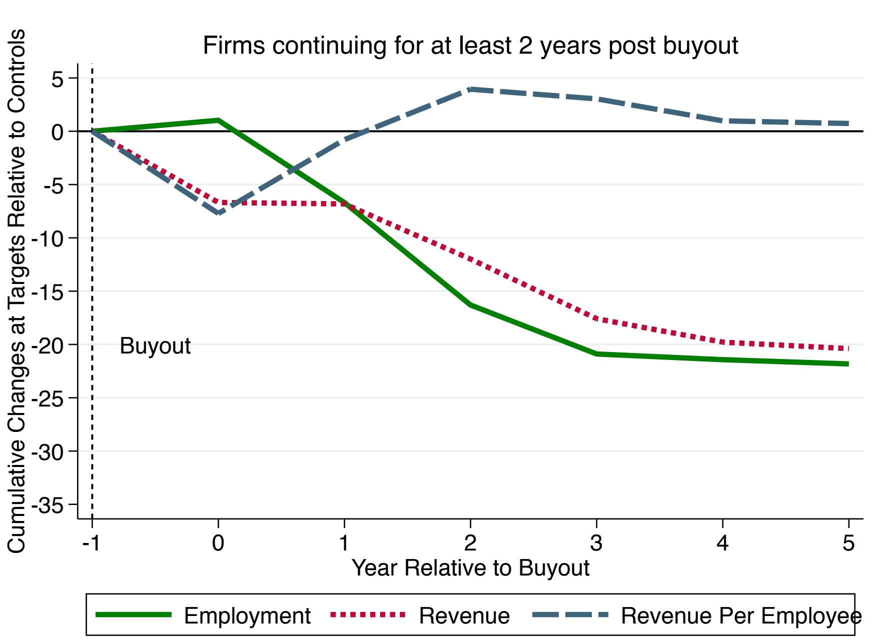
(D) Long Run Effects

Notes: Panels A-C show difference in difference coefficients γ_j from equation 1. Table in panel D displays coefficients γ of the difference in difference specification:

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

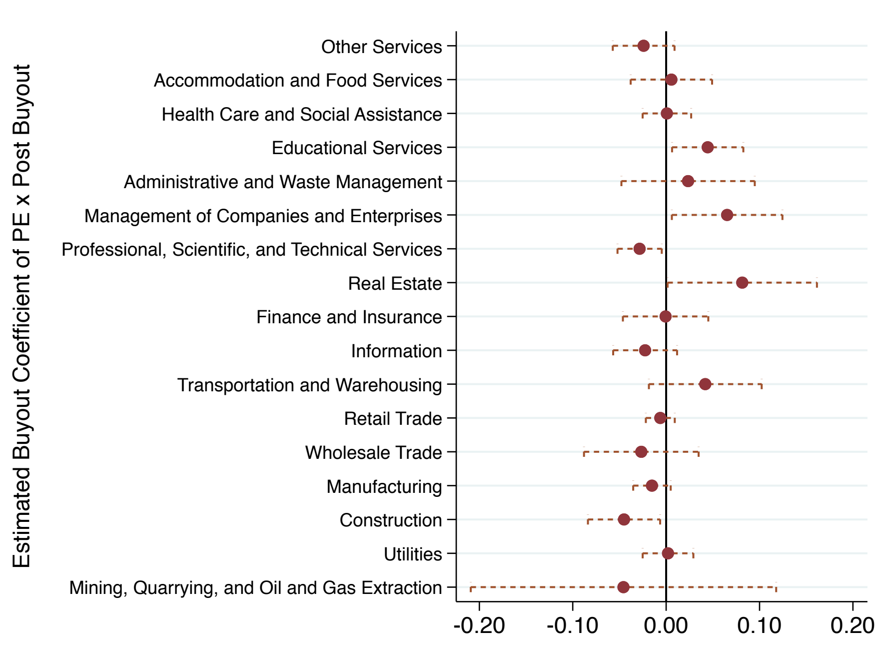
D_{cit} are dummies for a fully saturated interacted fixed effects of firm characteristics: industry, age, size, type of unit, and buyout year. Regression estimates are weighted by employment in buyout year t. For robustness, regressions are also weighted by employment in year $t-3$ relative to buyout, and give similar results (not reported). Standard errors are clustered at the firm level to account for potential heterogeneity. Dotted red lines show 90% confidence intervals. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure 21. Cumulated Changes for Two Year Continuing Firms, PE Deals 1997-2018

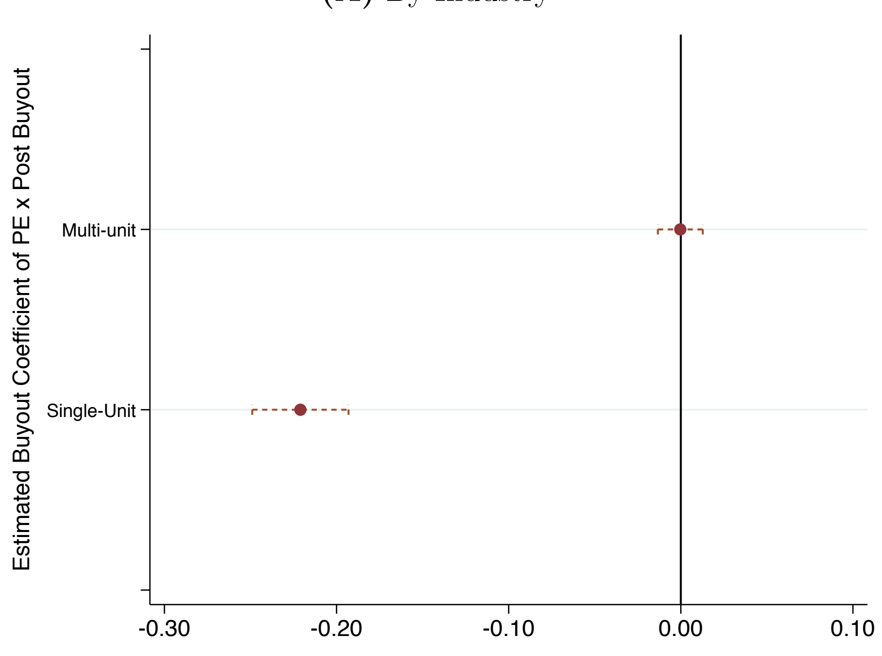


Notes: The figure plots changes five years post buyout by cumulating coefficients in figure 20 panels A-C. The coefficients are normalized to 0 in year -1 relative to buyout.

Figure 22. Estimated Difference in Difference Coefficient for Labor Productivity Growth Rates by Firm Industry and Type, PE Deals 1997 to 2018



(A) By Industry



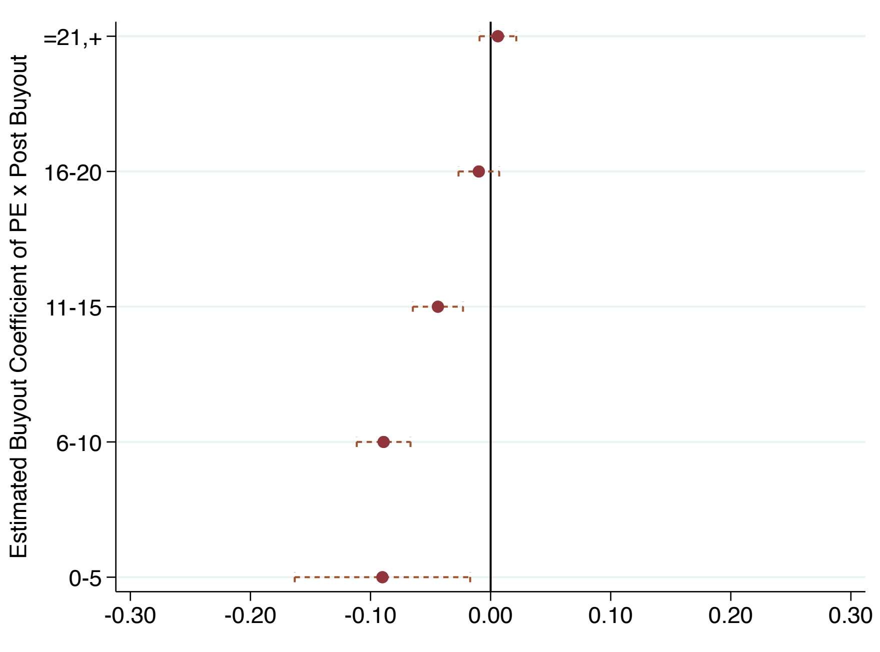
(B) By Type of Firm

Notes: This figure plots estimated labor productivity coefficients γ of the difference in difference specification:

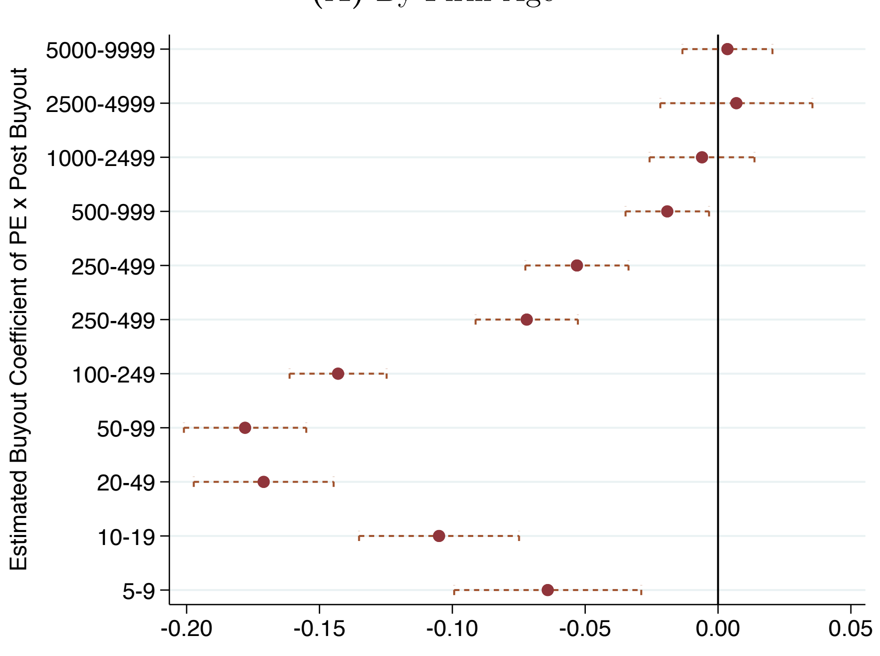
$$y_{it} = \alpha_t + \gamma(\text{PE}_i \times \text{Post}_{it}) + \sum_c \theta_c D_{cit} + \lambda_0 \text{LFIRM}_i + \varepsilon_{it}$$

by two digit NAICS industry code (panel A) and type of the firm: single unit or multi unit (panel B). The points show estimated coefficients, and lines show 90% confidence intervals. Regressions are weighted by employment in year of buyout. Using weights $t_0 - 3$ relative to buyout year gives similar results. Standard errors are clustered at the firm level. Coefficient for "Arts, Entertainment, and Recreation" (panel A) is not reported due to few firms and large standard errors.

Figure 23. Estimated Difference in Difference Coefficient for Labor Productivity Growth Rates by Firm Age and Size, PE Deals 1997 to 2018



(A) By Firm Age



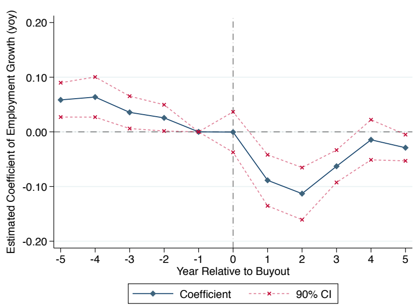
(B) By Firm Size

Notes: This figure plots estimated labor productivity coefficients γ of the difference in difference specification:

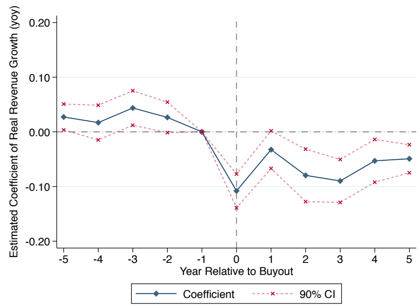
$$y_{it} = \alpha_t + \gamma(\text{PE}_i \times \text{Post}_{it}) + \sum_c \theta_c D_{cit} + \lambda_0 \text{LFIRM}_i + \varepsilon_{it}$$

by 5 firm age buckets based on firm employment (panel A), and 13 firm size categories based on firm employment in buyout year (panel B). The points show estimated coefficients, and lines show 90% confidence intervals. Regressions are weighted by employment in year of buyout. Using weights $t_0 - 3$ relative to buyout year gives similar results. Standard errors are clustered at the firm level.

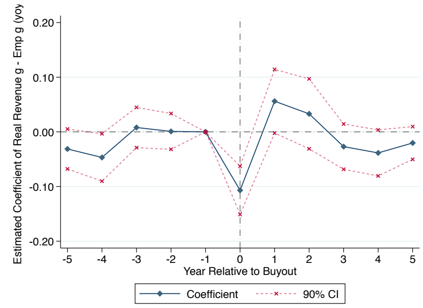
Figure 24. Dynamic Estimates of Post Buyout Over Time Relative to Buyout Year, PE Deals 1997-2018, All PE Targets



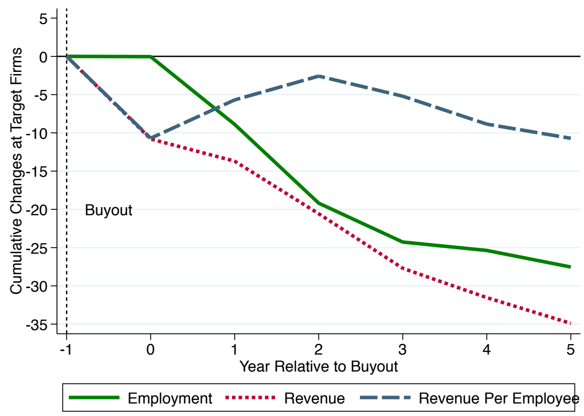
(A) Employment Growth



(B) Revenue Growth



(C) Labor Productivity



(D) Cumulated Changes

Notes: Panels A-C display coefficients $\alpha_{0,t}$ of the event study specification:

$$y_{it} = \alpha_t + \sum_{t=t_0-5, t\neq t_0-1}^{t=t_0+5} \alpha_{0,t} \text{Buyout}_{it} + \gamma \text{LFIRM}_{\ i} + \text{Fixed Effects} + \epsilon_{it} \tag{10}$$

Buyout_{it} takes value 1 for the year t relative to buyout year t_0 for firm i, bought by a PE fund. I omit the year before buyout $t_0 - 1$. The years post 5 years and pre 5 years of buyout are binned in $t = +5$ and $t = -5$ respectively. LFIRM_i is the growth rate of firm i from $t-3$ to $t-1$. Fixed Effects includes 18 two-digit NAICS industry codes, 13 firm size buckets, 5 firm age categories, and a dummy for multi-unit firm type. Standard errors are clustered at the firm level. Dotted red lines show 90% confidence intervals. Panel D cumulates growth rates in panels A-C.

Table 9. 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 5. 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 10. 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

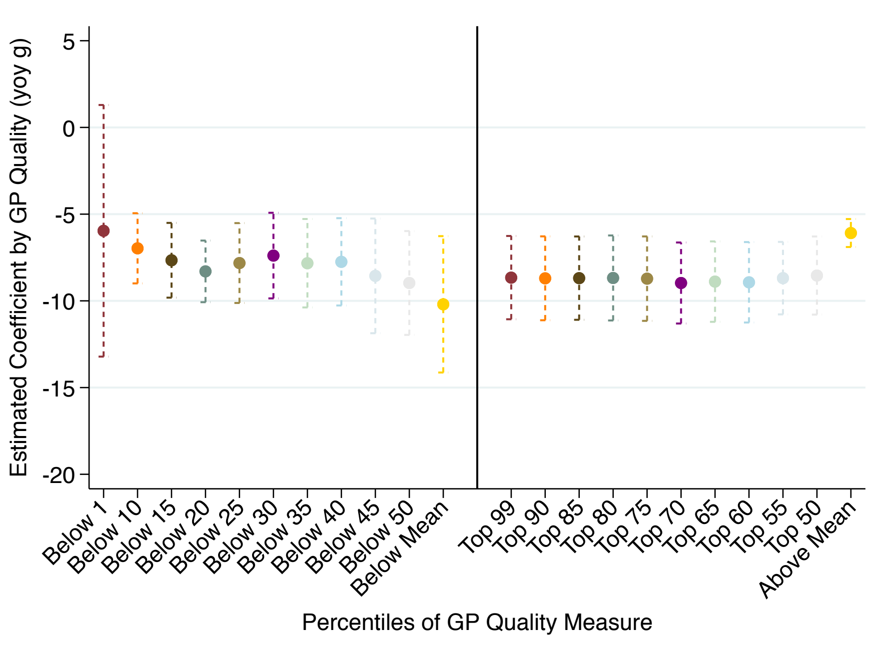
Notes: The table displays coefficients α_0 and β^r from specification 5. The regression consists of four categories: other investors, most underfunded, medium underfunded, and least underfunded public pension supported firms. Regression estimates are weighted by employment in buyout year t. Standard errors are clustered at the firm level to account for potential heterogeneity. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 11. Estimated Coefficients for Post Buyout by Pension Fund Underfunded Ratio, PE Deals 1997-2018

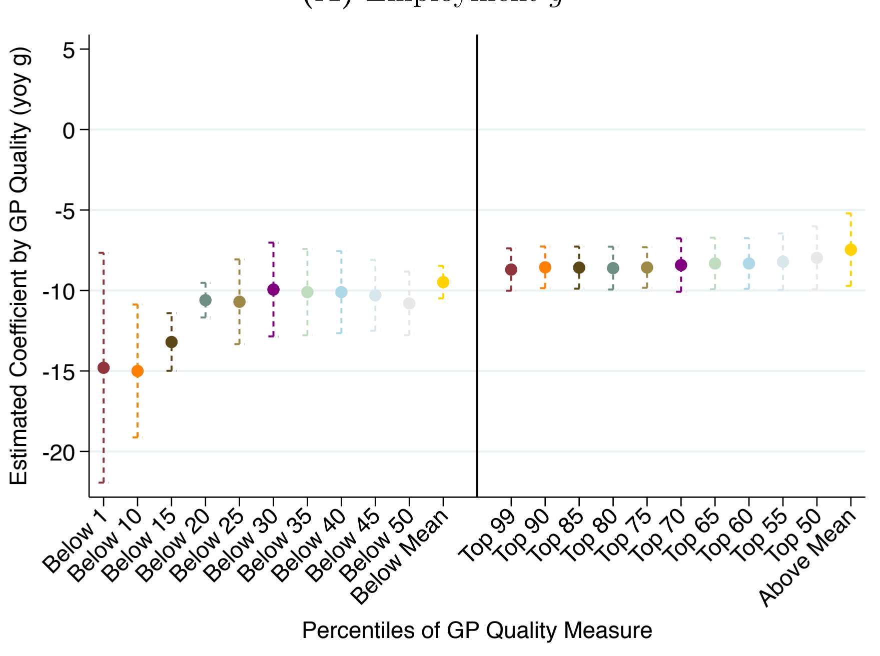
Dependent Variable:	Emp g (1)	Rev g (2)	Rev g-Emp g (3)
	Panel A: Pension Funded Ratio Split		
Post Buyout (Base: Least Underfunded)	-0.0570^{***}	-0.0700^{***}	-0.0130
	(0.0143)	(0.0126)	(0.0129)
Post Buyout $\times$ Most Underfunded	-0.0099	-0.0519^{***}	-0.0420^{**}
	(0.0140)	(0.0200)	(0.0188)
Post Buyout $\times$ 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 5. 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure 25. Estimates of Post Buyout × GP Quality Percentile, PE Deals 1997-2018



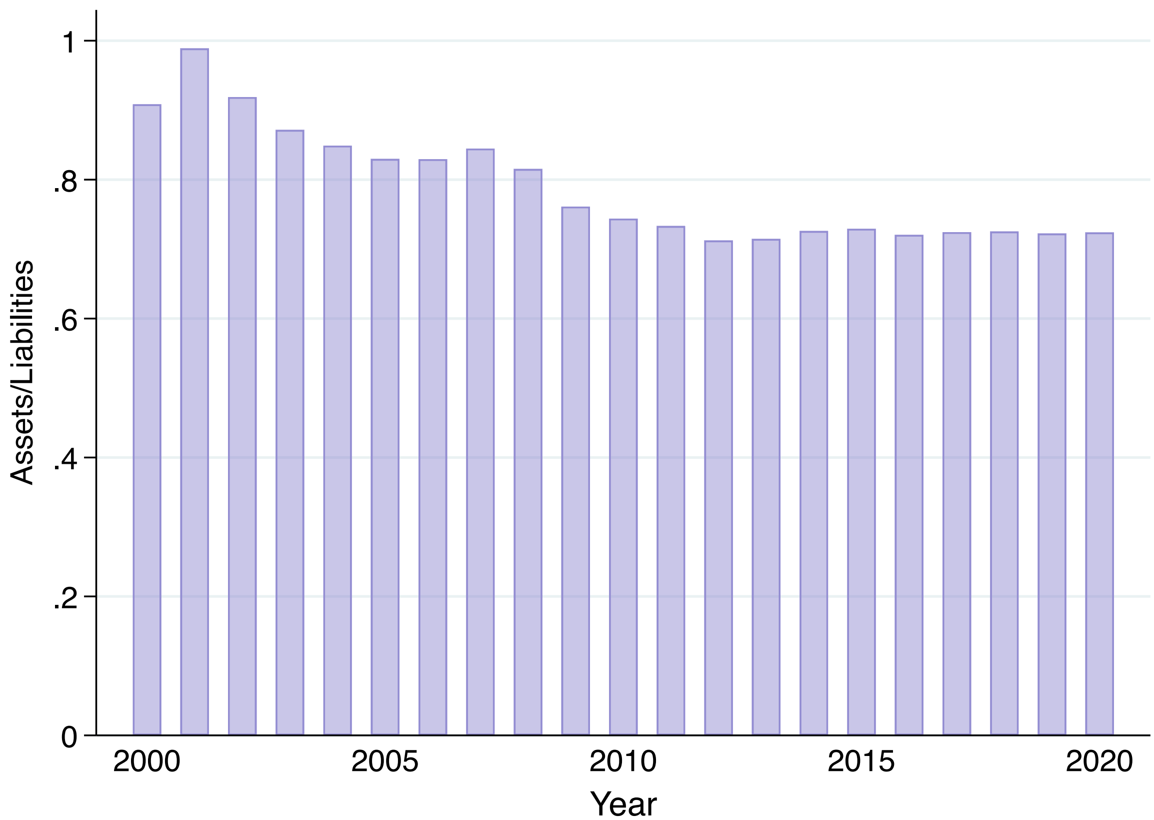
(A) Employment g



(B) Revenue g

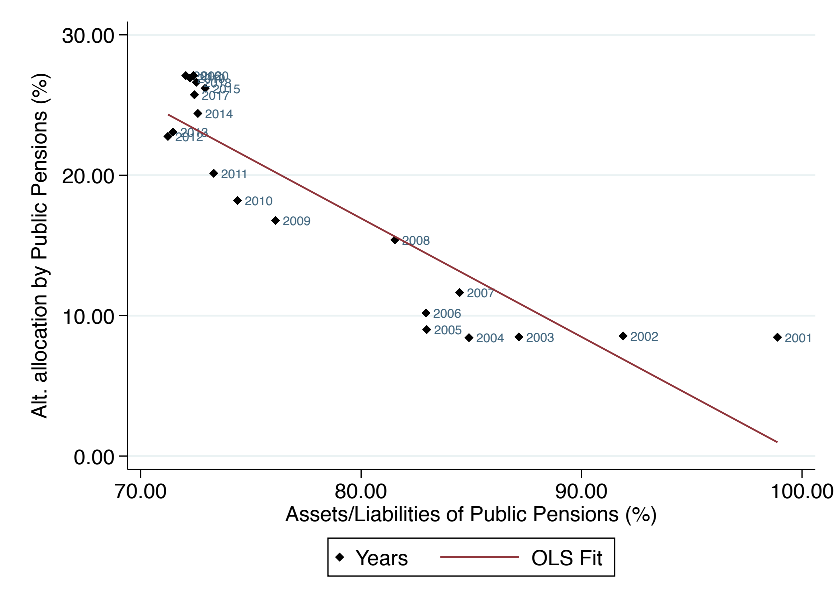
Notes: The figure shows estimates from equation 13, where GP_j is substituted with different percentile based splits of targets. Interaction term of $(\text{Post Buyout} \times \text{LP}_k)$ is omitted. Each color shows estimates from one regression. Panel A corresponds to employment growth rates, and panel B for revenue growth rates. Bars represent 90% confidence intervals.

Figure 26. Funded Positions of U.S. Public Pension Funds



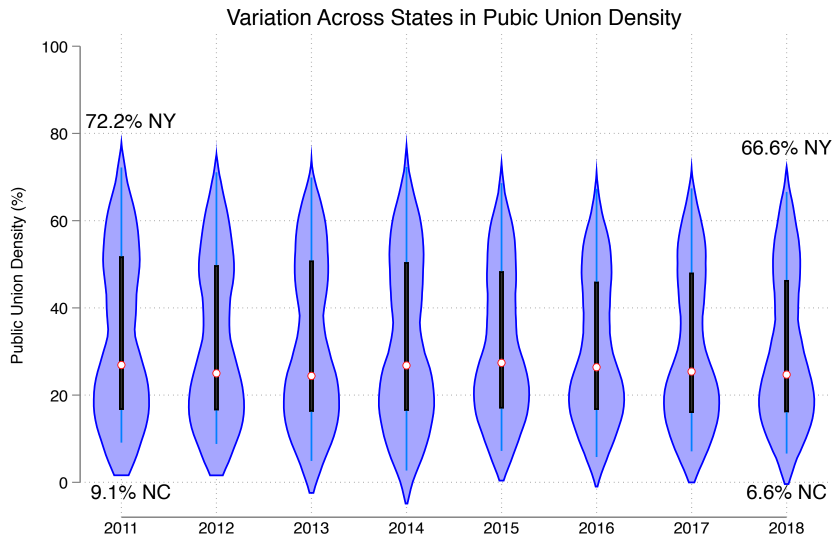
Notes: Funded positions are calculated as assets divided by liabilities. Liabilities in a year is the present discounted value of liabilities in the future. Source: Public Pensions Database.

Figure 27. Portfolio Allocations and Funded Positions of Public Pensions Over Years



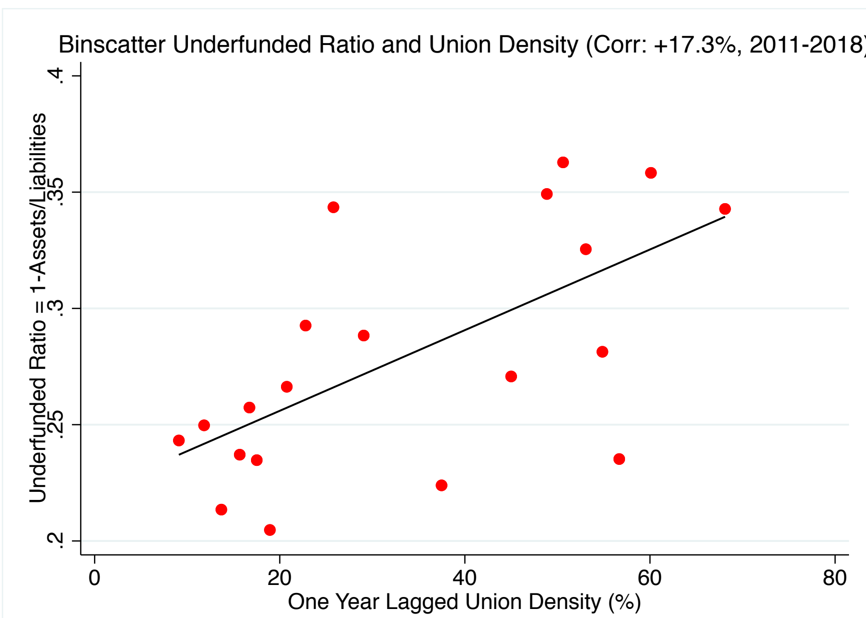
Notes: Portfolio allocations and funded positions of public pensions are sourced from Public Pensions Database, and interest rates from FRED.

Figure 28. Variation in Public Union Density Across States, 2011-2018



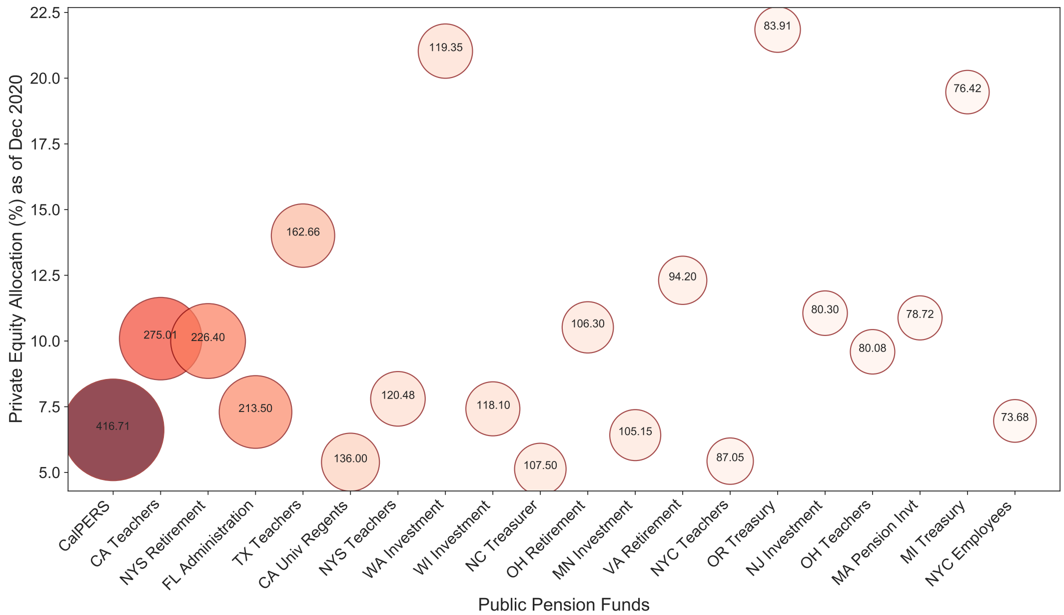
Notes: Figure shows variation in public union density across states over time. Public union density is defined as the percentage of public workers which are part of a union. Dispersion is similar for years not reported. Data are sourced from CPS and Union Stats.

Figure 29. Correlation Between Underfunded Ratio and One Year Lag Public Union Density

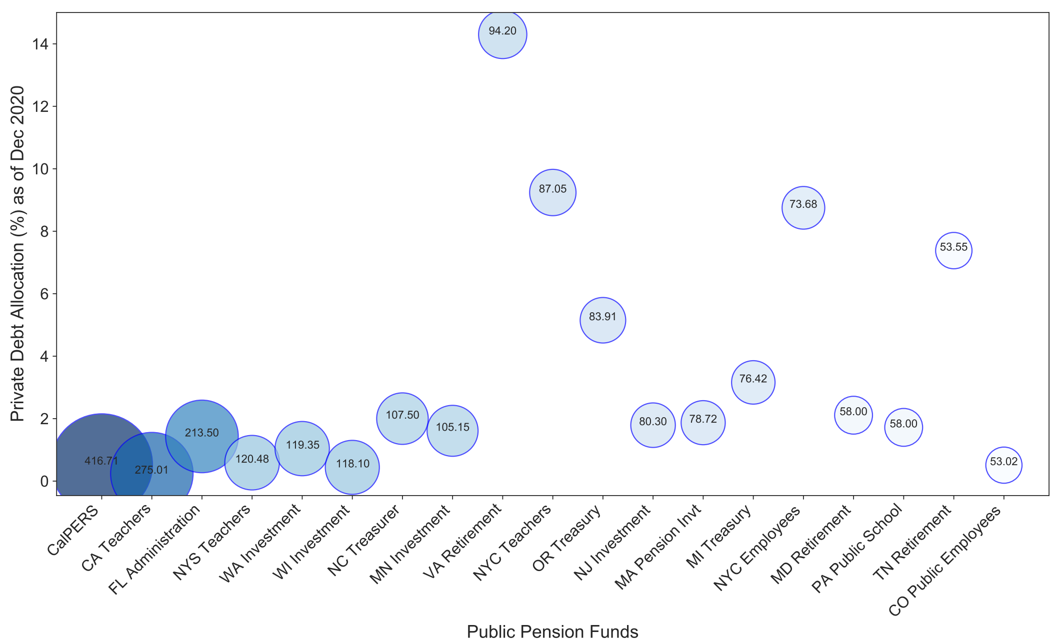


Notes: Figure plots a binscatter of underfunded ratio against one year lag of union density amongst public workers. Public union density is defined as the percentage of public workers which are part of a union. Underfunded ratio is one minus assets divided by liabilities for public pension plans. Figure 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 30. 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

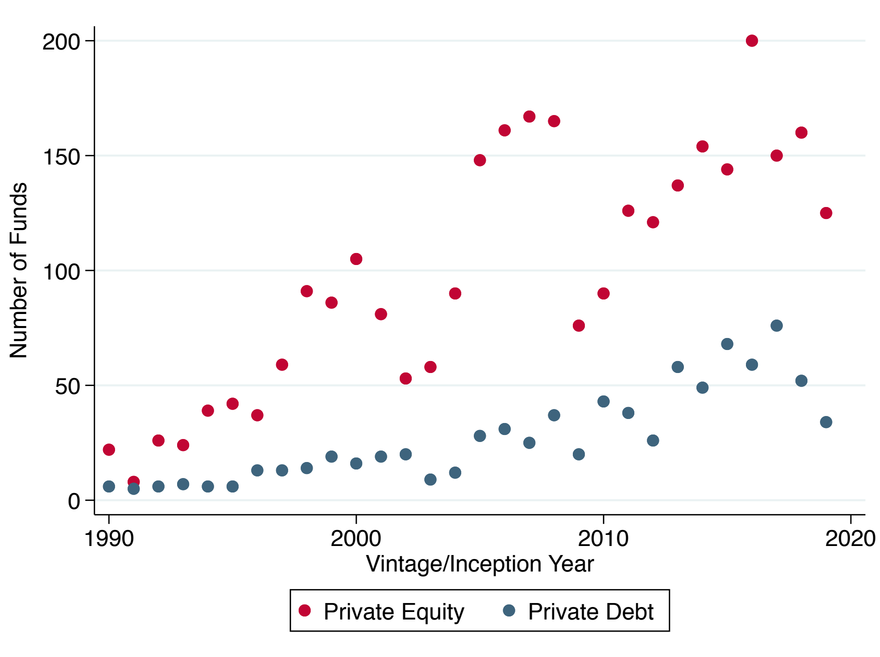
Notes: Allocations of public pension funds with assets under management (AUM) above \$50 mn. towards private equity (panel A) and private debt (panel B) as of December 2019. Size of the bubble corresponds to the size of the pension fund. Data are sourced from Preqin.

Table 12. 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.

Figure 31. Number of PE and PD Funds Over Years



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

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

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A Robustness of Aggregate Results

A.1 Uniform Treatment Effect From Davis et al. (2014)

I repeat my analysis with the uniform treatment effect regression specification used in Davis et al. (2014). The uniform treatment effect controls for industry × firm size × firm age × transaction year × type of unit (referred to as "cell"), and pre-buyout growth history.

$$y_{i,t+j} = \alpha_j + \sum_c \theta_{c,j} D_{cit} + \lambda_{0,j} \text{LFIRM}_i + \gamma_j \text{PE}_{it} + \varepsilon_{i,t+j}, \;\; j \in \{-5, \cdots, 5\} \tag{11}$$

where y_{it} is the outcome variable in year over year growth rates from $t + j - 1$ to $t + j$ for firm i, D_{cit} is the set of 5,600 dummy variables representing cell c for firm i at time t, LFIRM_i is the growth rate for firm i from $t - 3$ to $t - 1$, and PE_{it} is the dummy variable for a target firm. The coefficient of interest is the treatment effect γ_j. Standard errors are clustered at the firm level. Clustering at the cell level gives similar results. The regression is weighted by employment in the year of buyout.

At the firm level, table A.13 shows estimated coefficients for γ_j from specification 11 from years -5 to +5 relative to buyout. I find similar results to Figure 5.

Table A.13. Post Buyout Annual Growth Rates at Target Firms Relative to Controls, PE Deals 1997-2018

Dependent Variable:	(1) Emp g	Adj. R^2	(2) Pay g	Adj. R^2	(3) Revenue g	Adj. R^2	(4) Pay g-Emp g	Adj. R^2	(5) Rev g-Emp g	Adj. R^2	Obs. (Mn.)
-5	0.018		0.009		0.006		-0.009		-0.013		
	(0.023)	0.060	(0.018)	0.086	(0.016)	0.071	(0.014)	0.018	(0.030)	0.033	11.2
-4	0.038**		0.034*		0.019		-0.004		-0.019		
	(0.019)	0.065	(0.019)	0.093	(0.016)	0.078	(0.010)	0.018	(0.021)	0.030	12.6
-3	0.015		0.012		0.040**		-0.003		0.025		
	(0.015)	0.088	(0.015)	0.087	(0.016)	0.084	(0.013)	0.082	(0.017)	0.075	14.1
-2	0.005		-0.005		0.026***		-0.010		0.021		
	(0.009)	0.436	(0.011)	0.357	(0.013)	0.133	(0.008)	0.065	(0.013)	0.120	16.1
Buyout Year -1	-0.013		-0.019**		0.012		-0.006		0.025*		
	(0.008)	0.355	(0.009)	0.220	(0.013)	0.096	(0.006)	0.098	(0.015)	0.115	17.7
Buyout Year	-0.017		-0.012		-0.080***		0.005		-0.063***		
	(0.017)	0.064	(0.021)	0.047	(0.015)	0.048	(0.011)	0.050	(0.020)	0.057	18.3
Buyout Year +1	-0.067***		-0.061**		-0.022		0.006		0.045*		
	(0.024)	0.043	(0.025)	0.051	(0.015)	0.051	(0.013)	0.018	(0.027)	0.028	16.6
+2	-0.062**		-0.038		-0.032		0.023		0.030		
	(0.029)	0.032	(0.026)	0.047	(0.025)	0.048	(0.016)	0.018	(0.036)	0.021	13.8
+3	-0.024		-0.045*		-0.045**		-0.020		-0.021		
	(0.017)	0.035	(0.027)	0.049	(0.019)	0.049	(0.017)	0.020	(0.019)	0.026	11.5
+4	0.027		0.043**		-0.011		0.016		-0.038*		
	(0.018)	0.035	(0.021)	0.049	(0.022)	0.049	(0.012)	0.020	(0.021)	0.029	9.6
+5	-0.007		-0.019		-0.0004		-0.012		0.007		
	(0.015)	0.035	(0.016)	0.050	(0.016)	0.048	(0.011)	0.025	(0.022)	0.026	8.2
Cell FE	Y		Y		Y		Y		Y		
Lagged Firm g	Y		Y		Y		Y		Y		

Notes: The table displays coefficients γ_j in the regression specification 11

$$y_{i,t+j} = \alpha_j + \sum_c \theta_{c,j} D_{cit} + \lambda_{0,j} \text{LFIRM}_i + \gamma_j \text{PE}_{it} + \varepsilon_{i,t+j}, \quad j \in \{-5, \cdots, 5\}$$

D_{cit} are dummies for a fully saturated interacted fixed effects of firm characteristics: industry, age, size, type of unit, and buyout year. The number of observations decrease when estimating coefficients for years further out relative to the buyout year. All regressions are weighted by employment in year of buyout to account for business significance of units. Standard errors are clustered at the firm level. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A.2 Across Sample Periods

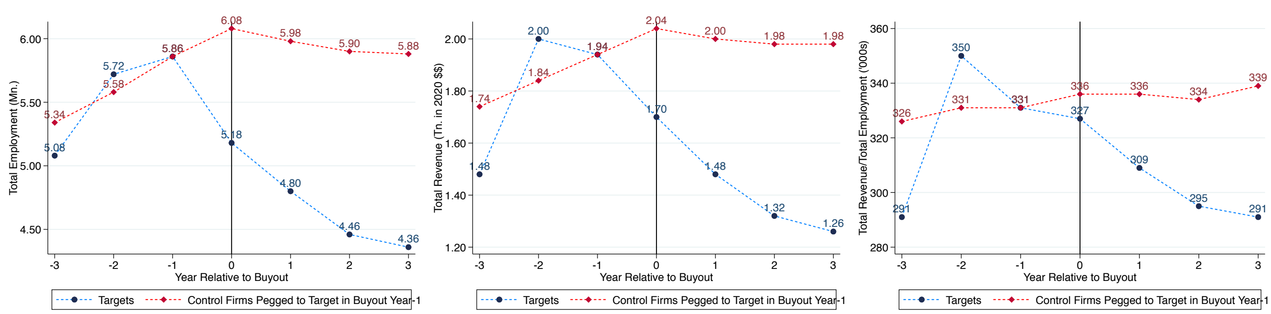
One concern is that since the main sample period ends in 2018, there isn't a full time period to track each target post buyout. This section conducts robustness of aggregate results over sample period 2000-2015, allowing for each firm to be tracked for three years respectively pre and post buyout.

To start, I show the total employment, total revenue, and revenue per employee numbers at target and control firms pre and post three years relative to buyout for PE deals from 2000 to 2015.[30] Figure A.32 shows total employment, revenue and revenue by employment for target firms and control firms scaled to targets in year $t_0 - 1$. Target firms reduce employment by

Target firms reduce employment by 1.5 mn jobs from 1 year before to 3 years after buyout, representing a 25.6% decline, while the control firms increase employment by 0.3% 3 years post buyout. Three years after, the number of employees at targets is below than the number of employees three years before. Revenue at targets decreases by 34.6%, while for controls it increases by 2.6%. Total Revenue by total employment decreases 12% for targets and increases 2.3% for controls.

Figure A.33 shows the dynamic and static difference in difference coefficients. The results are similar 5 which confirms that results are not driven by firms undergoing a buyout in later years and not having enough time to track them post buyout. The cumulative 3 year effect on labor productivity for targets is 0.01% relative to controls.

Figure A.32. U.S. PE Target and Controls, PE Deals: 2000-2015

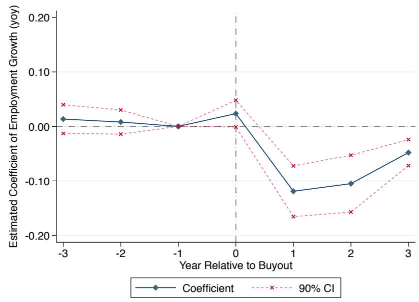


(A) Total Employment **(B)** Total Revenue **(C)** Total Rev/ Total Emp

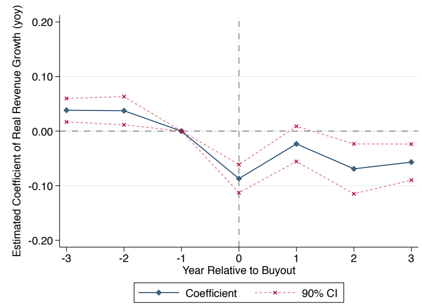
Notes: These figures show total employment (panel A), total revenue (panel B), and total revenue by total employment (panel C) 3 years pre and post buyout at firms. The blue line represents target firms and red line shows control firms scaled to value of target firms in year $t_0 - 1$ relative to buyout year t_0.

[30]The revenue data is available from 1997 to 2018, hence I allow firms to be tracked around a three year window choosing sample period: 2000-2015.

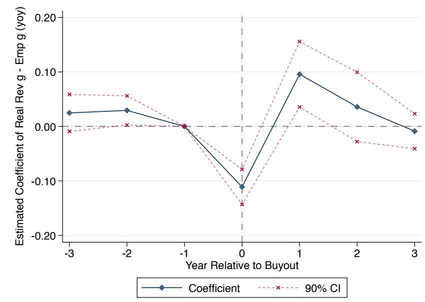
Figure A.33. U.S. PE Target and Controls, PE Deals: 2000-2015



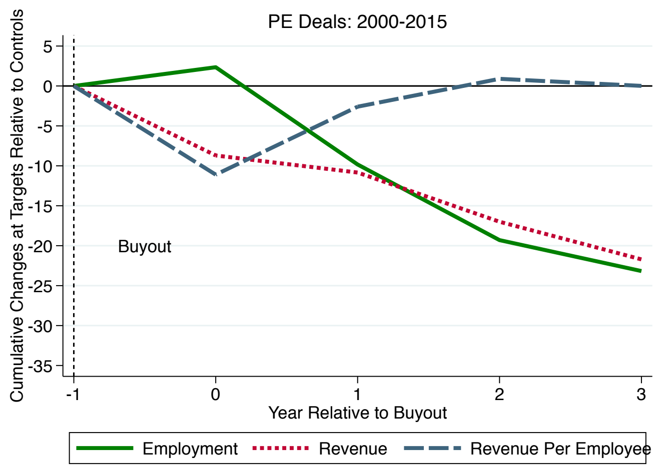
(A) Employment g



(B) Revenue g



(C) Rev g - Emp g



(D) Cumulative Changes

Dependent Variable:	Emp g (1)	Rev g (2)	Rev g-Emp g (3)
Treatment × Post Buyout	-0.0194^{**}	-0.0212^{***}	-0.0018
	(0.0088)	(0.0081)	(0.0089)
Industry × Age × Size × Type × Transaction Year FE	Y	Y	Y
Year FE	Y	Y	Y
Lagged Firm g	Y	Y	Y
Weighted Emp t_0	Y	Y	Y
Observations	18,060,000	18,060,000	18,060,000
Adjusted R^2	0.0340	0.0392	0.0081
Dependent Variable Mean	0.0091	0.0152	0.0061

(E) Long Run Effects

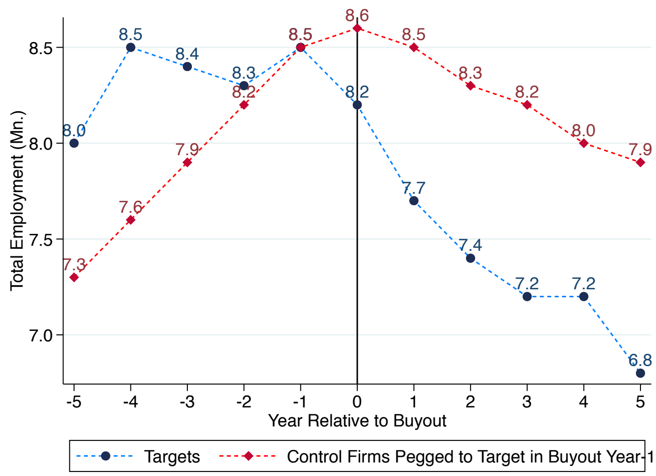
Notes: Panels A, B, and C show coefficients γ_j of the difference in difference specification:

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

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. Panel D cumulates changes in Panels A-C. Table in Panel E shows the long run effects γ. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

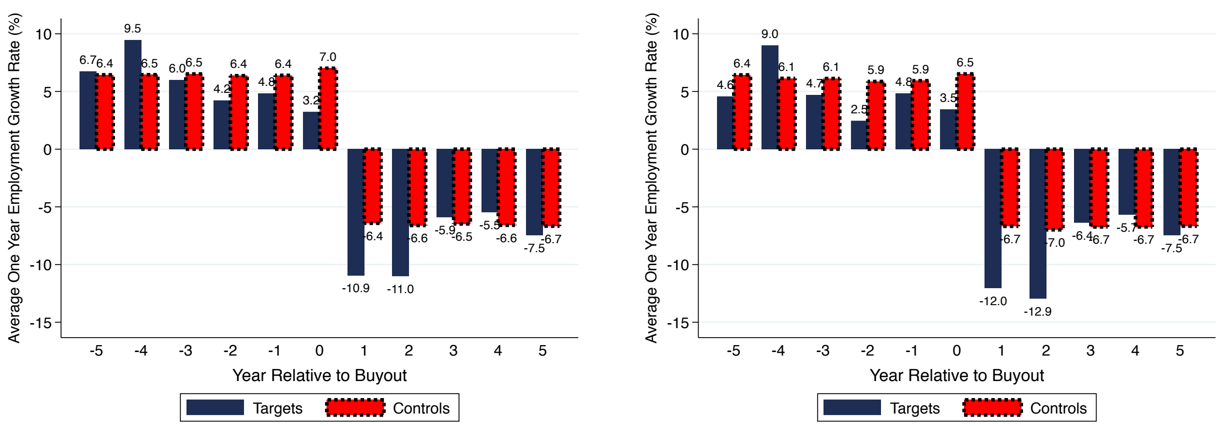
A.3 Employment Effects for a Longer Time Period

Figure A.34. Employment at Target and Control Firms Pre and Post Buyout, PE Deals 1979-2014



Notes: The figure show total employment 5 years pre and post buyout at target (blue) and control (red) firms. The control firms are scaled to value of target firms in year $t_0 - 1$. Control firms are comparable firms not targeted by PE funds. The controls are constructed based on a fully saturated interaction of 5,600 firm characterisitcs: industry, size, age, type of firm, and transaction year. Year 0 captures the effect of the buyout.

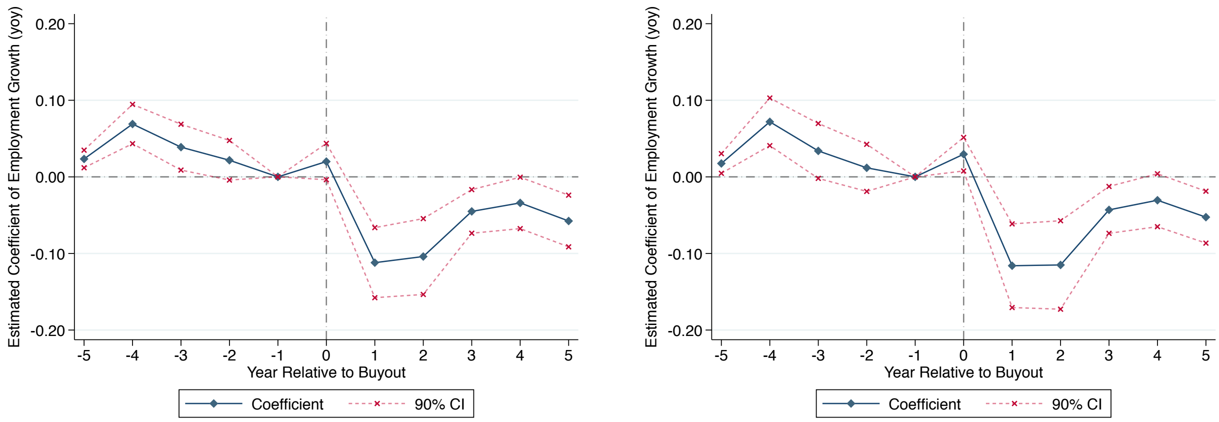
Figure A.35. Non Parametric: One Year Employment Growth Rate Relative to Buyout Year



(A) PE Deals 1979-2018 **(B)** PE Deals 1979-2014

Notes: This figure shows average one year employment growth rates at target and control firms pre and post buyout. The blue (left) bars represent targets and the red (right) bars represent controls. The target firms are entities which are bought by PE firms. Controls are comparable firms not targeted by PE funds. The controls are constructed based on a fully saturated interaction of firm characterisitcs: industry, size, age, type of firm, and transaction year. Year 0 captures the effect of the buyout. Panel A considers PE deals in 1979-2018, and panel B considers deals in 1979-2014.

Figure A.36. Difference in Difference Estimated Coefficients γ_j for Employment Growth Rates Over Time Relative to Buyout Year



(A) PE Deals 1979-2018 **(B)** PE Deals 1979-2014

Notes: Figures plot difference in difference coefficients γ_j from equation 1 for employment growth rates. Panel A considers PE deals from 1979-2018, and panel B considers deals in 1979-2014.

Table A.14. Number of Targets In Years Relative to Buyout, PE Deals 1979-2014

	Year Relative to Buyout:										
	-5	-4	-3	-2	-1	0	1	2	3	4	5
Number of Targets	4,600	4,800	5,100	5,300	5,400	5,400	4,900	3,700	3,300	3,000	2,700

Notes: The table shows number of firms in years -5 to +5 relative to buyout year. PE deals from 1979-2014 are considered.

Figure A.35 shows one year employment growth rates for target and control firms considering PE deals from 1979 to 2019 (panel A) and 1979 to 2014 (panel B). I find similar results for deals from 2001-2014.

Table A.15. Estimated Coefficients of Post Buyout Employment Growth Rate

Panel **(A)** 1979-2018

	(1)	(2)	(3)	(4)	(5)
Post Buyout	-0.287^{***}	-0.177^{***}	-0.133^{***}	-0.156^{***}	-0.119^{***}
	(0.005)	(0.020)	(0.014)	(0.018)	(0.013)
Year FE	Y	Y	Y	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	Y	Y	Y
Weighted Emp t_0		Y	Y	Y	Y
Observations	$154,000$	$140,000$	$140,000$	$140,000$	$140,000$
Adjusted R^2	0.0623	0.0684	0.2870	0.0810	0.2960
Dependent Variable Mean	0.0382	0.0356	0.0356	0.0356	0.0356

Panel **(B)** 1979-2014

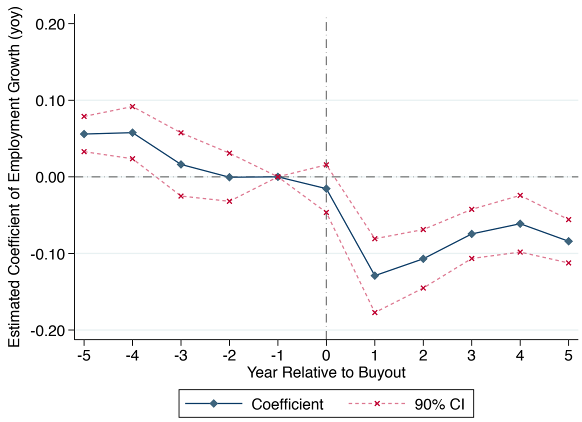
	(1)	(2)	(3)	(4)	(5)
Post Buyout	-0.277^{***}	-0.177^{***}	-0.135^{***}	-0.156^{***}	-0.119^{***}
	(0.006)	(0.022)	(0.016)	(0.022)	(0.013)
Year FE	Y	Y	Y	Y	Y
Firm Size FE			Y		Y
Firm Age FE			Y		Y
Industry FE				Y	Y
Type of Unit FE				Y	Y
Lagged Firm g	Y	Y	Y	Y	Y
Weighted Emp t_0		Y	Y	Y	Y
Observations	102,000	93,500	93,500	93,500	93,500
Adjusted R^2	0.0615	0.0756	0.3270	0.0894	0.3370
Dependent Variable Mean	0.0298	0.0238	0.0238	0.0238	0.0238

Notes: The table displays coefficients α_0 of the event study specification 3:

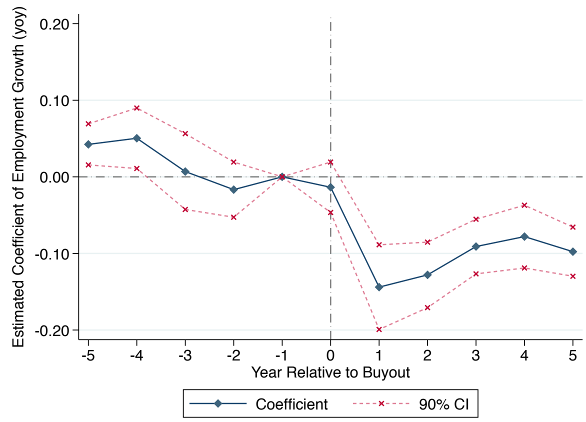
$$y_{it} = \alpha_t + \alpha_0 \text{Post Buyout}_{it} + \gamma \text{LFIRM}_i + \text{Industry FE} + \text{Firm Size FE} + \text{Firm Age FE} + \text{Type of Unit FE} + \epsilon_{it}$$

Post Buyout$_{it}$ takes value 1 for year t in which firm i is bought by a PE fund, and years following the buyout year. LFIRM$_i$ is the growth rate of firm i from $t_0 - 3$ to $t_0 - 1$. Industry FE consists of 18 two-digit NAICS codes, Firm Size FE captures 13 size buckets, Firm Age FE consists of 5 age categories, and Type of Unit FE is a dummy for multi-unit firm type. Columns have varying degree of fixed effects. Standard errors are clustered at the firm level. Panel A considers PE deals 1979-2018, panel B considers deals in 1979-2014. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure A.37. Dynamic Estimates of Post Buyout Over Time Relative to Buyout Year



(A) PE Deals from 1979-2018



(B) PE Deals from 1979-2014

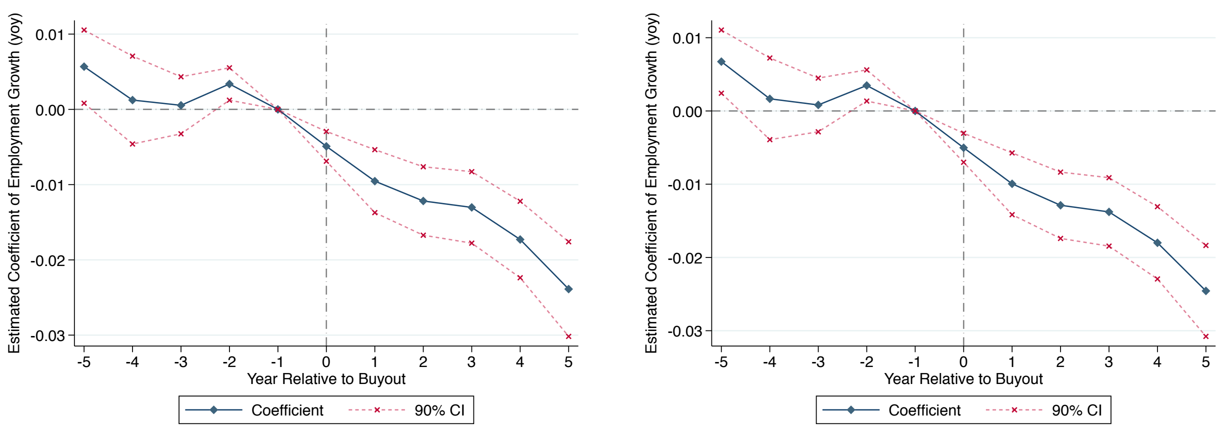
Notes: Figures show dynamic event study estimates of employment growth rates from specification 10 five years pre and post buyout. Year $t_0 - 1$ is omitted. Standard errors are clustered at the firm level. Dotted red lines show 10% confidence intervals. Panel A considers deals in 1979-2018, and panel B considers deals in 1979-2014.

A.4 Using Alternate Employment Data from Revelio Labs

To confirm the post buyout employment declines, I use another data provider, Revelio which sources its data from online job postings, government publications etc. The data is available at a monthly frequency from 2008 onwards. To make comparisons with results using Census micro-data, I use March as the year end, study five years pre and post buyout, and follow same adjustments as with the Census data.

Figure A.38 shows specification 10 with year fixed effects (panel A), and year and industry fixed effects (panel B). Standard errors are clustered at the firm level.

Figure A.38. Dynamic Estimates of Post Buyout Over Time Relative to Buyout Year, PE Deals from 2008-2021



(A) Year Fixed Effects **(B)** Year, Industry Fixed Effects

Notes: Figures show dynamic event study estimates of employment growth rates from specification 10 five years pre and post buyout. Year $t_0 - 1$ is omitted. Standard errors are clustered at the firm level. Dotted red lines show 90% confidence intervals. Panel A includes year fixed effects, and panel B includes year and industry fixed effects.

While the sample period and data is different, both panels show a significant 8% decline in employment upto five years post buyout. This confirms the result in the main text.

A.5 Different Random Samples using Census Micro-Data

Table A.16. 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:

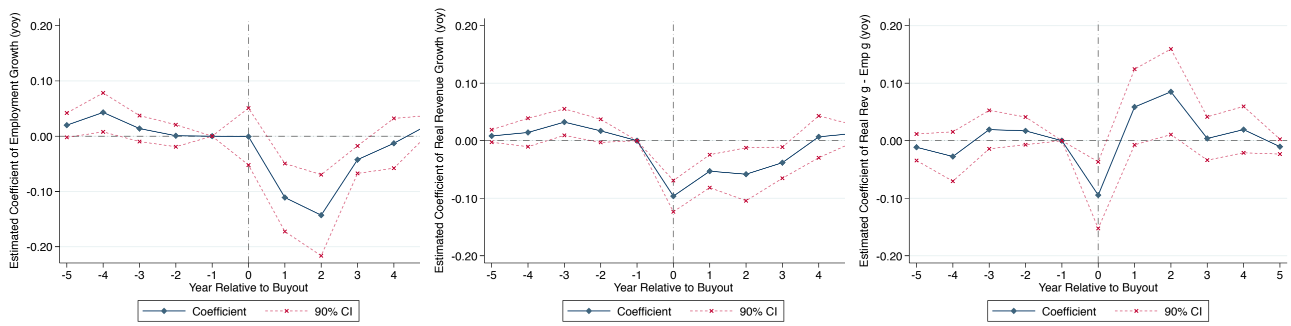
$$y_{it} = \alpha_t + \gamma(\text{PE}_i \times \text{Post}_{it}) + \sum_c \theta_c D_{cit} + \lambda_0 \text{LFIRM}_i + \varepsilon_{it}$$

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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A.6 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 5 and table 2, I also control for lagged one year revenue controls for revenue growth effects. Figure A.39 shows similar results for both versions of the difference in difference.

Figure A.39. 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 1:

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

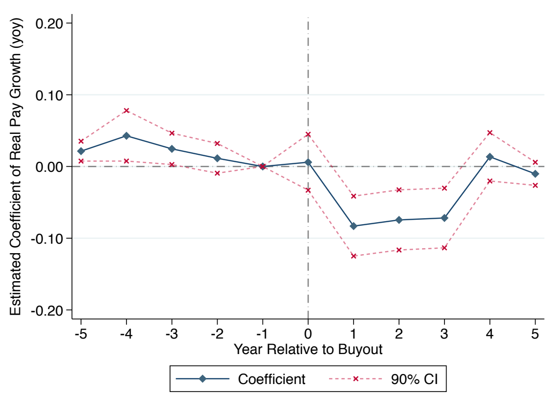
D_{cit} are dummies for a fully saturated interacted fixed effects of firm characteristics: industry, age, size, type of unit, and buyout year. Regression estimates are weighted by employment in buyout year t. Standard errors are clustered at the firm level. Dotted red lines show 90% confidence intervals.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

B Additional Analysis of Aggregate Results

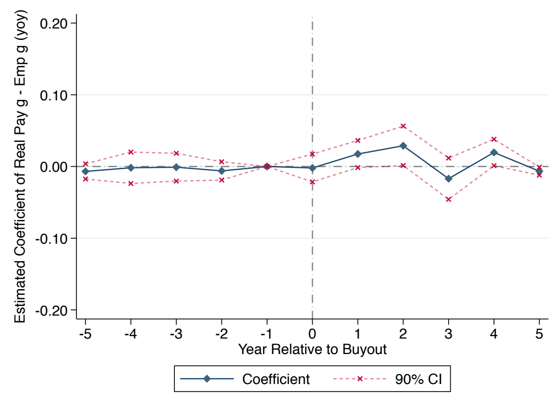
B.1 Pay and Pay Per Employee

Further, I study the total pay in real 2020 dollar terms, and pay per employee post buyout. I find substantial decreases in pay along with employment post buyout. I find no substantial changes in pay per employee. This shows that workers across distributions are being laid off.

Figure B.40. Difference in Difference Estimated Coefficients γ_j Over Time Relative to Buyout Year, PE Deals 1997-2018



(A) Real Pay g



(B) Pay g - Emp g

Dependent Variable:	Pay g (1)	Pay g-Emp g (2)
Treatment × Post Buyout	-0.0263^{***}	0.0011
	(0.0087)	(0.0029)
Industry × Age × Size × Type × Transaction Year FE	Y	Y
Year FE	Y	Y
Lagged Firm g	Y	Y
Weighted Emp t_0	Y	Y
Observations	$25,430,000$	$25,430,000$
Adjusted R^2	0.0528	0.0087
Dependent Variable Mean	0.0139	0.0042

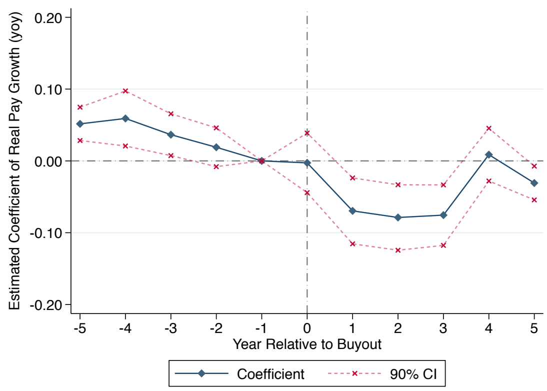
(C) Long Run Effects

Notes: Panels A and B show coefficients γ_j of the difference in difference specification 1:

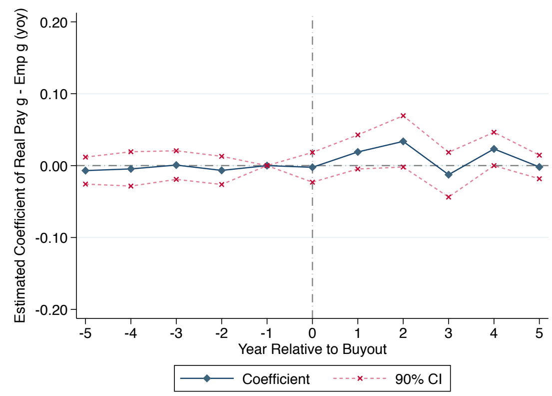
$$y_{it} = \alpha_t + \sum_{j=-5, j\neq -1}^{j=+5} \gamma_j (\text{PE}_i \times \text{Buyout Year}_{it_0+j}) + \sum_c \theta_c D_{cit} + \lambda_0 \text{LFIRM}_i + \varepsilon_{it}$$

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 C shows the long run effects γ. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table B.17. Event Study Estimated Coefficients of Post Buyout, PE Deals 1997-2018



(A) Real Pay g



(B) Pay g - Emp g

Dependent Variable:	Pay g (1)	Pay g -Emp g (2)
Post Buyout	-0.075^{***}	0.009
	(0.016)	(0.007)
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
Observations	$70,000$	$70,000$
Adjusted R^2	0.193	0.016
Dependent Variable Mean	0.028	0.005

(C) Long Run Effects

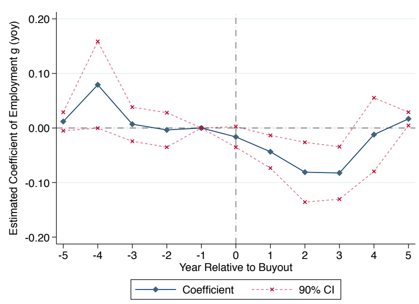
Notes: The table shows coefficients α_0 of the event study specification 3:

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

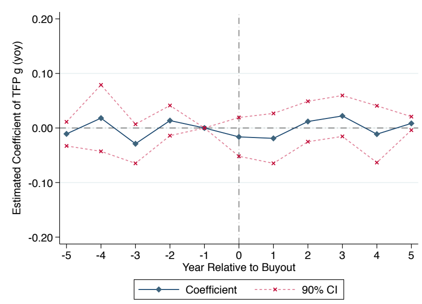
LFIRM_i is lagged firm growth rate between year -3 and -1 relative to buyout. Fixed Effects includes 12 firm size categories, 5 firm age cateogories, 22 two-digit industry SIC codes, and a dummy for multi/single unit firm. Standard errors are clustered at the firm level. Dotted red lines show 90% confidence intervals. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

B.2 Manufacturing Targets

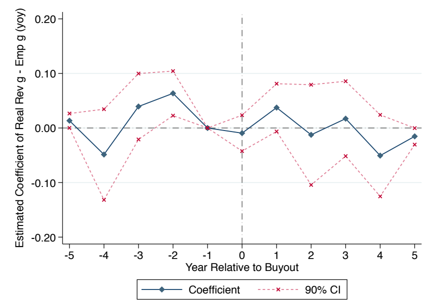
Figure B.41. Difference in Difference Estimated Coefficients γ_j for Manufacturing Firms Over Time Relative to Buyout Year, PE Deals 1997-2018



(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 1 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

B.3 Tracking Workers Post Buyout

The earlier sections study effects on employment which includes employees across the wage distribution – CEOs, top managers, and hour based contract employees. We still don't know how workers at different pay structures are affected when their firm is targeted by pivate equity.

Following Song, Price, Guvenen, Bloom and von Wachter (2018), I construct wage dispersion measures at firm level. Within firm i wage dispersion at time t can be expressed as the sum of squared differences of individual worker's wage from the average firm wage at each time t,

$$\text{var}_{it}(y_{wit}|_{w\in i}) = \sum_{w} \Big(y_{wit} - \overline{y}_{it}\Big)^2 \tag{12}$$

This variance is conditional of workers being employes at the firm. Each worker has equal weight. I consider firm year observations with at least 20 employees to allow for sufficient variation within firm.

Table B.18. Estimated Difference in Difference Coeffcients γ for Within Firm Wage Dispersion Over Time Relative to Buyout Year, PE Deals 1979-2018

Dependent Variable:	Within Firm Variance (1)	Inter Quartile Range (2)
Treatment × Post Buyout	0.169**	0.099*
	(0.075)	(0.057)
Industry × Age × Size × Type × Transaction Year FE	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
Controls	Y	Y
Weighted Emp t_0	Y	Y
Observations	Under Disclosure	Under Disclosure
Adjusted R^2	0.606	0.673
Dependent Variable Mean	2.084	1.727

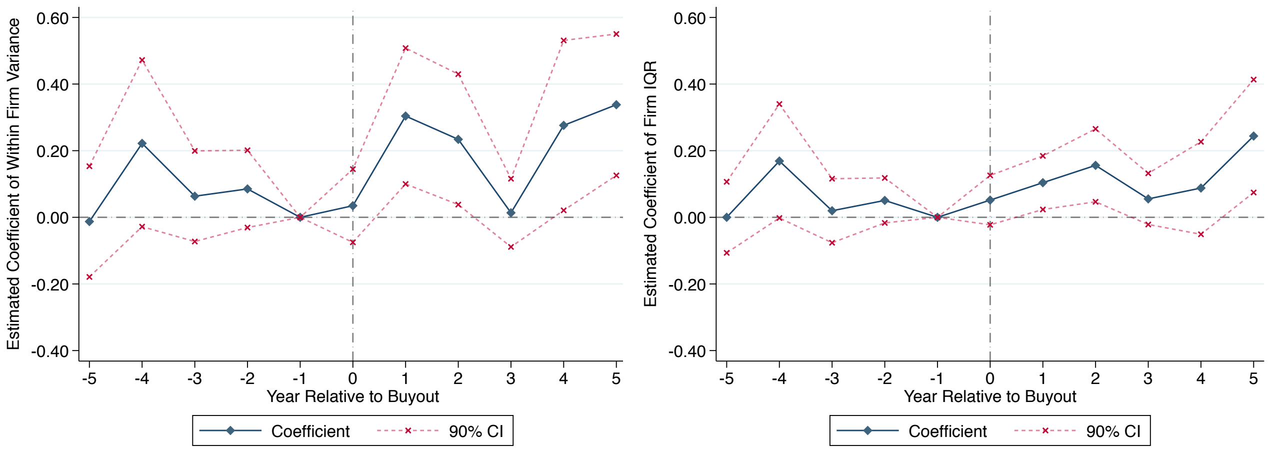
Notes: The table displays coefficients γ of the difference in difference specification:

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

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. 27 states are used in the regression. Standard errors are clustered at the firm level to account for potential heterogeneity. Number of obversations are under disclosure at the Census. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure B.42 panel A and B show within firm variation and inter-quartile range of log

Figure B.42. Estimated Difference in Difference Coeffcients γ_j for Within Firm Wage Dispersion Over Time Relative to Buyout Year, PE Deals 1979 to 2018



(A) Within Firm Variance **(B)** Within Firm Inter Quartile Range

Notes: Figures show coefficients γ_j of the difference in difference specification 1. Panel A has dependent variable as within firm wage variance, and panel B has dependent variable as within firm wage inter quartile range. 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. Standard errors are clustered at the firm level. Dotted red lines represent 90% confidence intervals. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

earnings within a firm increases post buyout. This suggests that the workers in the middle of the firm wage distribution are laid off in a PE buyout.

C Additional Investor Heterogeneity Results

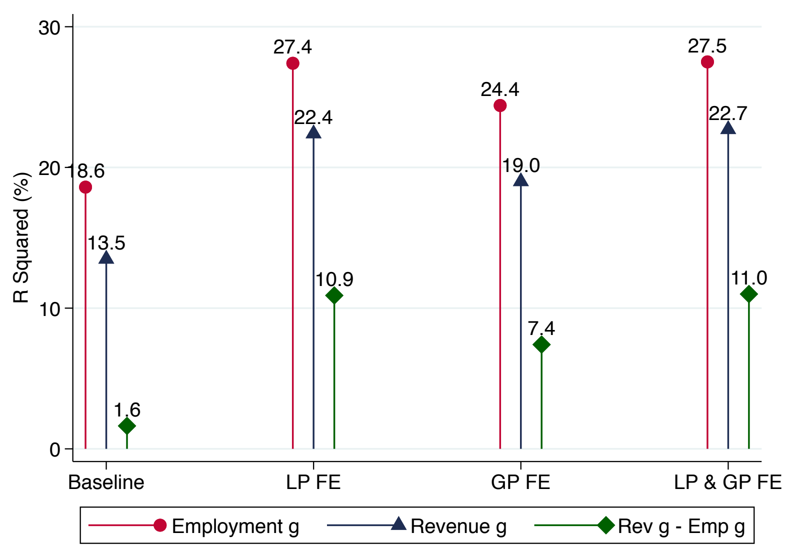
C.1 Model Explanatory Power: Abowd et al. (1999) Approach

I study the explanatory power of the model for target's revenue, employment, and labor productivity growth rates post buyout when including LP and GP identities involved in the deal, in an approach similar to Abowd et al. (1999). I add LP and GP interactions with Post Buyout$_{it}$ in specification 3:

$$y_{it} = \alpha_t + \alpha_0 \text{Post Buyout}_{it} + \sum_j \beta_j \Big(\text{Post Buyout}_{it} \times \text{GP}_j\Big) + \sum_k \beta_k \Big(\text{Post Buyout}_{it} \times \text{LP}_k\Big) + \gamma \text{LFIRM}_i + \text{Fixed Effects} + \epsilon_{it} \tag{13}$$

Figure C.43 shows the model fit using the R squared for different models. The R squared for explaining labor productivity growth rate post buyout increases from 1.6% to 10.9% with LP identities interacted with Post Buyout. I also see significant increases for explaining revenue and employment growth rates. This lends support that the source of capital plays a significant role in studying the effects on target firms post buyout.

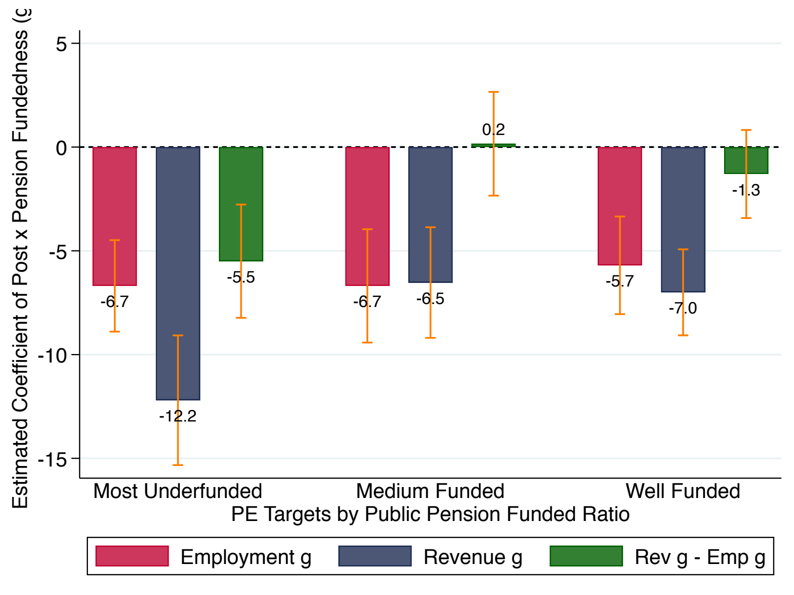
Figure C.43. Model Explanatory Power for Real Outcomes at Targets Under Different Specifications



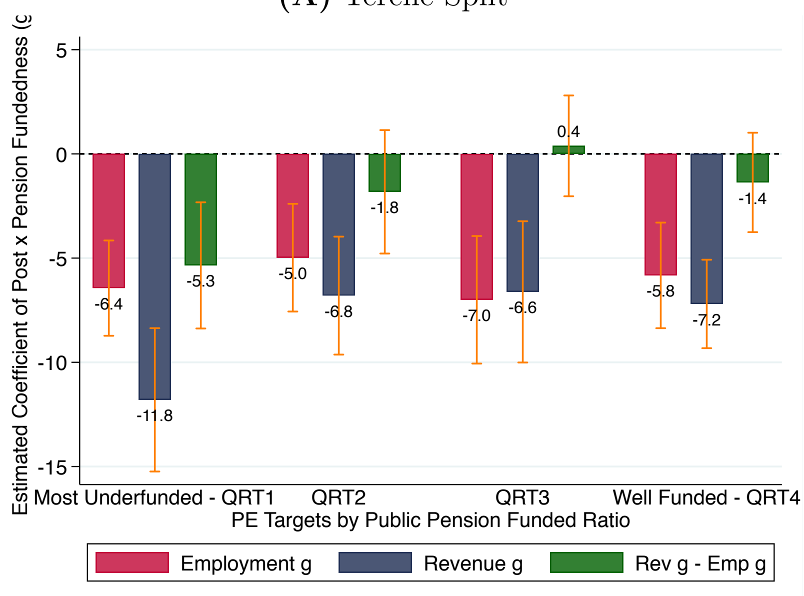
Notes: "Baseline" refers to equation 3, "LP FE" considers only heterogeneity based on LP and omits the interaction term $\big(\text{Post Buyout}_{it} \times \text{GP}_j\big)$ from equation 13, "GP FE" considers only heterogeneity based on GP and omits the interaction term $\big(\text{Post Buyout}_{it} \times \text{LP}_k\big)$ from equation 13, and "LP & GP FE" is equation 13. PE deals are from 1997 to 2018.

C.2 Only Public Pension Supported Firms

Figure C.44. Estimates of Post Buyout × Underfunded Ratio, PE Deals 1997-2018



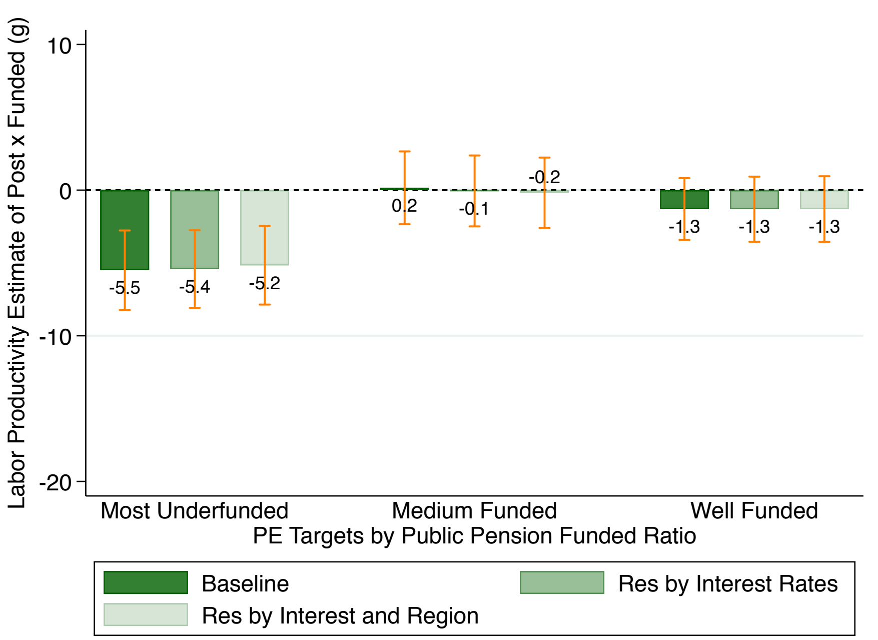
(A) Tercile Split



(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 5 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 C.45. Labor Productivity Estimates of Post Buyout × Underfunded Ratio, Residualized for Macroeconomic Conditions, PE Deals 1997-2018

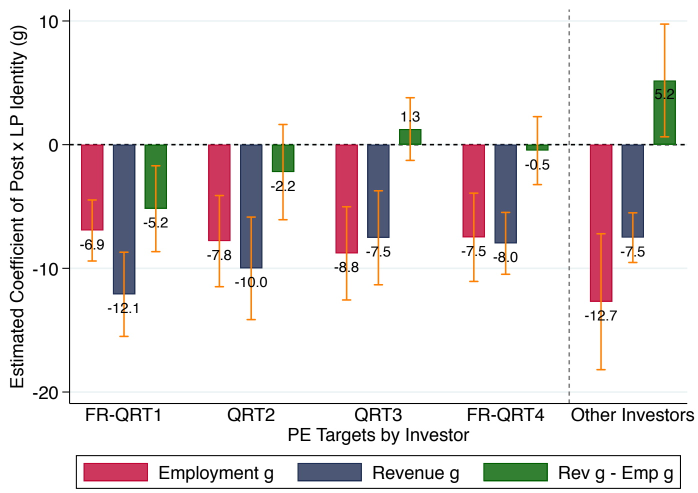


Notes: The figure plots estimated coefficients for labor productivity growth rates of Post × Pension Underfunded Split in equation 5 for each tercile of firms. Different shades of bars correspond to underfunded ratios of pensions post *residualizing* for different macroeconomic conditions. Firms are 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.

C.3 Additional Splits

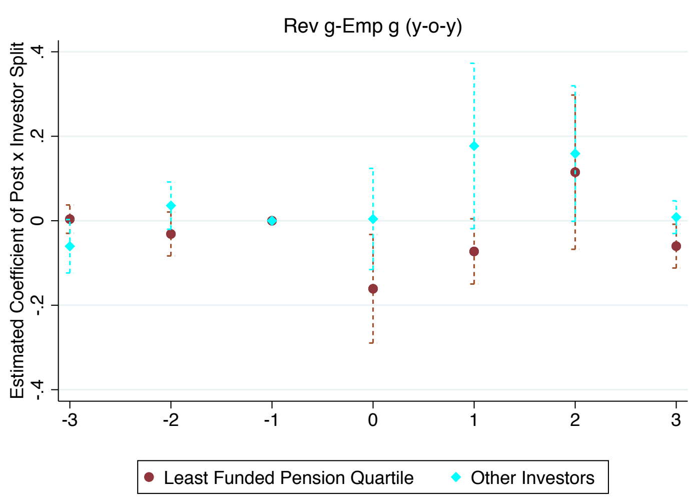
In specification 5, I split the data in terciles of different underfunded ratios. In this section, I confirm the result using quartile splits and find similar patterns. Figure C.46 shows that the most underfunded public pensions supporting significant decreases in labor productivity is not driven by chioce of splits.

Figure C.46. Estimates of Post Buyout × Investor Type, PE Deals 1997-2018



Notes: The figure plots estimated coefficients from equation 5 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 C.47. 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 5 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.

D GP Quality Heterogeneity

D.1 Book Value Measure of GP Skill

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.

$$\text{Assets}_{\mathcal{J},t} = \sum_{j \in \mathcal{J}} \text{Assets}_{j,t} \tag{14}$$

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.

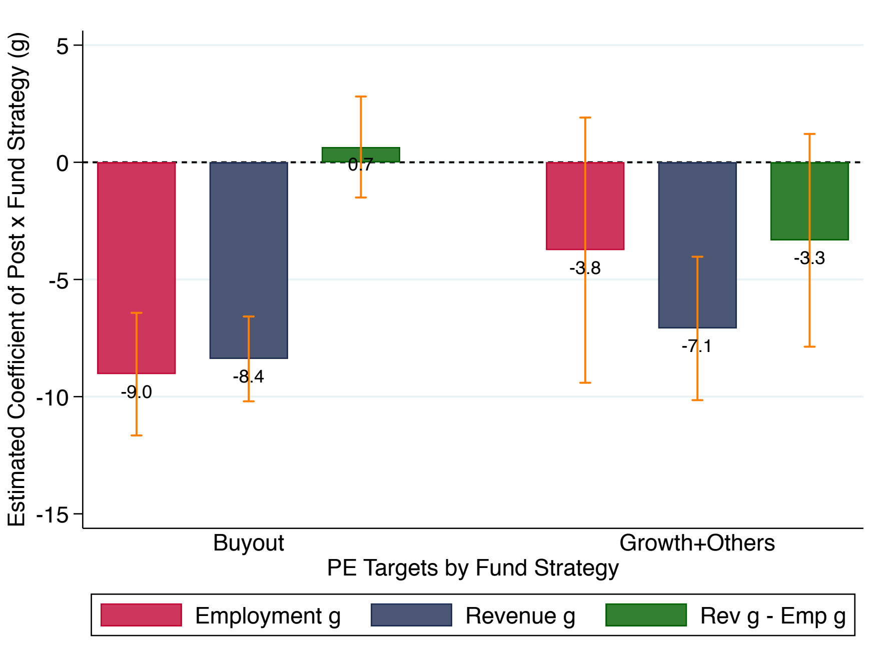
D.2 Additional Results on GP Heterogeneity

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 D.48 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 D.48. 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 5. 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.

E 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[31], 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`.

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

F Sample Construction

F.1 Cleaning Preqin and Merging Across Preqin Datasets

F.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.

F.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.

F.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.

F.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".[32] Second, I keep targets in the U.S..

[32] 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 F.1.1, F.1.2, and F.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.

F.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 F.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.[33] 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.[34]

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

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

[34] 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.

F.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 F.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 1 shows the matched and unmatched targets by year, Figure 18 shows by industry and state. The stringent match methodology explains the conservative matches.

F.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.

F.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).

F.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.

G Variable Construction

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

G.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.

$$Y_{eit} = F(K_{eit}, L_{eit}, M_{eit}) \tag{15}$$

The production function 15 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,

$$\ln \text{TFP}_{eit} = \ln Y_{eit} - \alpha_K \ln K_{eit} - \alpha_L \ln L_{eit} - \alpha_M \ln M_{eit} \tag{16}$$

I define each of the inputs in equation 16 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.

$$\begin{aligned} Y_{eit} &= \frac{\text{TVS}_{eit} + (\text{TIE}_{eit} - \text{TIB}_{eit}) + (\text{WIE}_{eit} - \text{WIB}_{eit})}{\text{PISHIP}_t}, \quad \text{if } Y_{eit} > 0 \\ Y_{eit} &= \frac{\text{TVS}_{eit}}{\text{PISHIP}_t}, \quad \text{otherwise} \end{aligned} \tag{17}$$

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.

$$K_{eit} = K_{eit-1} \times (1 - \delta_{it}) + I_{eit} \tag{18}$$

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.

$$\text{KEQ}_{eit} = \text{KEQ}_{eit-1} \cdot (1 - \text{EQDPR}_{it}) + \frac{\text{NM}_{eit}}{\text{PIINVE}} \tag{19}$$

$$\text{KST}_{eit} = \text{KST}_{eit-1} \cdot (1 - \text{STDPR}_{it}) + \frac{\text{NB}_{eit}}{\text{PIINVS}} \tag{20}$$

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.

$$\text{K}_{eit} = \text{K}_{eit-1} \cdot (1 - \text{EQDPR}_{it}) + \frac{\text{TCE}_{eit}}{\text{PIINVE}} \tag{21}$$

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.

$$\text{KEQ}^{initial}_{eit} = \frac{\text{MAE}_{eit} \cdot (\text{NKCEQ}_{eit}/\text{GKHEQ}_{eit})}{\text{PIINVE}} \tag{22}$$

$$\text{KST}^{initial}_{eit} = \frac{\text{BAE}_{eit} \cdot (\text{NKCST}_{eit}/\text{GKHST}_{eit})}{\text{PIINVS}} \tag{23}$$

$$\mathrm{K}_{eit}^{initial} = \frac{\mathrm{TAE}_{eit} \cdot (\mathrm{NKCEQ}_{eit}/\mathrm{GKHEQ}_{eit})}{\mathrm{PIINVE}} \tag{24}$$

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 19-21 and 22-24, 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).

$$\begin{aligned} \mathrm{TH}_{eit} &= \frac{\mathrm{PH}_{eit} \times \mathrm{SW}_{eit}}{\mathrm{WW}_{eit}}, \quad \text{if } \mathrm{SW}_{eit} > 0, \ \mathrm{WW}_{eit} > 0 \\ \mathrm{TH}_{eit} &= \mathrm{PH}_{eit}, \quad \text{otherwise} \end{aligned} \tag{25}$$

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}.

$$\mathrm{CM}_{eit} = \underbrace{\mathrm{CP}_{eit} + \mathrm{CR}_{eit} + \mathrm{CW}_{eit}}_{\equiv \mathrm{NE}_{eit}} + \underbrace{\mathrm{EE}_{eit} + \mathrm{CF}_{eit}}_{\equiv \mathrm{E}_{eit}} \tag{26}$$

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.

$$\mathrm{M}_{eit} = \frac{\mathrm{CP}_{eit} + \mathrm{CR}_{eit} + \mathrm{CW}_{eit}}{\mathrm{PIMAT}_t} + \frac{\mathrm{EE}_{eit} + \mathrm{CF}_{eit}}{\mathrm{PIEN}_t} \tag{27}$$

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 16 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.

$$TC_{eit} = L_{eit} + M_{eit} \tag{28}$$

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.

$$\pi_{eit} = \frac{\text{TVS}_{eit} - \text{TC}_{eit}}{\text{TVS}_{eit}} \tag{29}$$

Firm Level.

$$\pi_{it} = \sum_{e} w_{eit}\pi_{eit} \tag{30}$$

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.

G.2 Worker Pay Variables

For accurate measurement of within firm wage dispersion, I subset to observations with at least 20 employees at a firm-year. Let y_{wit} be the log earnings of worker w employed by firm i in period t. I construct two measures of wage dispersion.

First, following Song et al. (2018) I construct wage dispersion measures at the firm level. Within firm wage dispersion at time t can be written as the sum of squared differences of individual worker's wage from the average firm wage at time t:

$$\text{var}_{it}(y_{wit}|_{w\in i}) = \sum_{w} \Big(y_{wit} - \overline{y}_{it} \Big)^2 \tag{31}$$

$\text{var}_i(y_{wit}|_{w\in i})$ is the variance of worker earnings within a firm i at time t, conditional on the worker being employed at the firm. This is under the assumption that each worker has equal weight in the firm.

Additional information about earnings within a firm can be obtained by studying percentiles of the earnings distribution within a firm-year. For this, I consider a second metric which is the interquartile range of employee wages.

$$\text{IQR}_{it} = y_{wit}^{p75} - y_{wit}^{p25} \tag{32}$$

where, y_{wit}^{p75} and y_{wit}^{p25} represents the 75th and 25th percentile of wages within a firm-year.