Essays in Private Capital

Vrinda Mittal

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Abstract

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This thesis titled “Essays in Private Capital” comprises of three essays focused on various parts of private capital. Private capital, also known as alternative assets are non-traded, broadly defined as private equity, real estate, venture capital, hedge funds, infrastructure and natural resource investments. The first chapter studies private equity, the second focuses on residential real estate, and the third is on commercial real estate. These are important asset classes given the low interest rate environment, and the recent COVID-19 and Silicon Valley Bank crisis which had large exposures to private assets.

The first essay titled “Desperate Capital Breeds Productivity Loss: Evidence from Public Pension Investments in Private Equity” studies investor heterogeneity in private equity and its ultimate effect on target firms. Using novel micro-data on individual investments in private equity funds and buyout deals combined with confidential Census data, I show that capital contributed by the most underfunded U.S. public pensions decreases efficiency at target firms, as pensions fuel the growth of low quality, new entrant private equity funds. These results get stronger post the financial crisis, when underfunded positions and their subsequent investments in private equity increased. The paper shows that traditionally positive post buyout efficiency results turn negative in recent years, as marginal investors matching with marginal private equity funds pull down the average. The most underfunded pensions also realize lower total private equity returns relative to the least underfunded ones. These results suggest possibility of a “funding doom loop” as currently public pensions use assumed return on assets to calculate liabilities.

The second essay titled “Flattening the Curve: Pandemic-Induced Revaluation of Urban Real Estate” focuses on work from home with the onset of the COVID-19 pandemic and its effect on
residential real estate prices across the U.S. We show that the COVID-19 pandemic brought house price and rent declines in city centers, and price and rent increases away from the center, thereby flattening the bid-rent curve in most U.S. metropolitan areas. Across MSAs, the flattening of the curve is larger where working from home is more prevalent, housing markets are more regulated, and supply is less elastic. Using a model predicting future residential price and rent evolution, we show urban revival in housing markets for the foreseeable future with urban rent growth exceeding suburban rent growth, as working from home recedes.

In the third essay titled “Work From Home and the Office Real Estate Apocalypse”, we show remote work led to large drops in lease revenues, occupancy, lease renewal rates, and market rents in the commercial office sector. We revalue New York City office buildings taking into account both the cash flow and discount rate implications of these shocks, and find a 39% decline in long run value. For the U.S., we find a $413 billion value destruction. We show evidence of flight to quality, as higher quality buildings are buffered against these trends, while lower quality office is at risk of becoming a stranded asset. These valuation changes have repercussions for local public finances and financial stability.

Dissertation Committee
Stijn Van Nieuwerburgh (Advisor), Professor of Finance and Earle W. Kazis and Benjamin Schore Professor of Real Estate, Columbia University
Xavier Giroud (Moderator), Roger F. Murray Associate Professor of Finance, Columbia University
Olivier Darmouni, Associate Professor of Finance, Columbia University
Wei Jiang, Asa Griggs Candler Professor of Finance, Emory University
Tano Santos, Robert Heilbrunn Professor of Asset Management and Finance, Columbia University
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Preface

I wrote “Essays in Private Capital” given the growing amount of investments in non-traded private assets by institutional and retail investors through different financial intermediaries such as private equity, real estate, venture capital, and infrastructure funds. The asset class is decentralized, and consists of varied structures. With a low interest rate environment and a need for long term investing, it is important to understand how the assets are performing and what the investors are earning. U.S. public pensions invested 27% of their assets in alternatives in 2020, higher than their fixed income allocations. I was intrigued to see where this capital is ultimately going, and if it’s beneficial to the end recipients. This inspired Chapter 1 of the dissertation. Moreover, with the recent COVID-19 pandemic and changes in work policies at firms – more remote work now vs. before the pandemic – the need for understanding how assets are affected is crucial. With remote work, residential and office real estate is directly hit, and a large part of real estate is not traded and consequently has difficult valuation methods. This motivated Chapter 2 and Chapter 3.

This field has important implications for financial markets and policy, and many open questions are yet to be answered. The recent Silicon Valley Bank failure in March 2023 had large exposures to venture capital funds. Private equity funds also invest in real estate, and real estate is affected with the onset of remote work, which ultimately affects investors investing in these funds. What do these exposures to non-traded assets mean for financial stability? Should there be procedures which oversee private assets, and if so, what should they be? Research in private assets is limited compared to other areas of finance and economics due to sparse data. The papers develop novel datasets as part of the research process. I hope to continue research in these areas, and hope these chapters foster future research.
Chapter 1: Desperate Capital Breeds Productivity Loss: Evidence from Public Pension Investments in Private Equity

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.

1This chapter is based on Mittal (2022), my academic job market paper. The paper is also cited in media sources such as Regulatory Compliance Watch. I am deeply indebted to my advisors: Stijn Van Nieuwerburgh (chair), Xavier Giroud, Wei Jiang, Olivier Darmouni, and Tano Santos for their continued support. I am extremely grateful to Emil Siriwardane and Harvard Business School for supporting my research. I benefited from interactions with Jonathan Zandberg (discussant), Lauren Cohen, Kent Daniel, Wenxin Du, Francesco Ferrante, Robin Greenwood, Ben Hyman, Victoria Ivashina, Anil Jain, Josh Lerner, Aditi Mittal, Jonathan Parker, Giorgia Piacentino, Or Shachar, Jose Scheinkman, Yuqi Zhang, and seminar participants at BIS, Boston College, CMU Tepper, Columbia Business School, Columbia Economics Department, Cornell Finance, Cornell Applied Economics, Duke Fuqua, Emory Goizueta, Federal Reserve Bank of New York, Federal Reserve Board of Governors, LBS, LSE, Michigan Ross, NYU Stern, Oxford Said, Rice Jones, UIUC Gies, and UNC Kenan-Flagler. I thank Jerome A. Chazen Institute, Eugene Lang Center, Sanford Bernstein Center, and Columbia Business School Finance Department for their financial support towards this project. I thank Sara Rothman from Preqin, and Shirley Liu from Census Bureau for their data support. Any views expressed are those of the author, and not of the U.S. Census Bureau. The Census Bureau’s Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2570 (CBDRB-FY23-P2570-R10172). Any errors are my own.
1.1 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. On the other hand, American Investment Council advocates that PE supports small business investments and jobs. 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 families (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.

\[\text{2Refer here. Another evidence is in article "Why work has failed us: Because companies aren’t sharing the profits" which mentions that Toys “R” Us employees were expected to stop working and apply for unemployment (link).}\]

\[\text{3For discussion, refer to Investment Council site (link).}\]
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 et al. (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 a focus on labor productivity considering all U.S. target firms in my sample which underwent a PE buyout from 1997 to 2018. 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. My estimates are similar to Davis et al. (2019) which finds a +7.5% two year productivity gain.

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4 Labor productivity measures are available from 1997 to 2018.
5 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.
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 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. 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.

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6This number over represents the involvement of public pensions in PE funds. However, Brown et al. (2015) shows comparability across databases which does not refute the importance of public pensions in PE.
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 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.\footnote{\textsuperscript{7}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 et al. (2022) documents preferential access of capital between top LPs and top GPs).}

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 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 worsens 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 et al. (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); Gupta and Van Nieuwerburgh (2021) study fund returns, Kaplan, Klebanov, and Sorensen (2012) 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 (2004) for investors’ liquidity considerations, and Begnau 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 (2023); 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) shows 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 under-funded 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 1.2 gives an overview of the data and presents institutional details. Section 1.3 presents productivity effects of PE buyouts in the aggregate. Section 1.4 shows trends in public pension investments over time, and Section 1.5 documents heterogeneity in real outcomes based on LP and GP types. Sections 1.6 and 1.7 discuss matching between LPs and GPs, and identification respectively. Section 1.8 discusses economic and policy implications. Section 1.9 concludes.

1.2 Data and Institutional Background

1.2.1 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.

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 et al. (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\footnote{I thank Anand Systla for FOIA data collection efforts.} 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.
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. 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. 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). 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 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.

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9 SSEL updates names and addresses every year from 1976 to 2019. An establishment is the unit of observation in SSEL.
10 Merge is robust based firm characteristics one to two years pre-buyout.
11 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.
Figure 1.1 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.\textsuperscript{12} Figure 1.2 shows employment and real revenue in 2020 U.S. dollars at matched targets as a percent of all LBD over time, while Figure 1.17 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 1.18 shows matched and unmatched firms have similar coverage by industry and state.

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.\textsuperscript{13} The employer-employee data is provided by the

\textsuperscript{12}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.

\textsuperscript{13}I have access to 27 states for worker level pay. This is generally the number of states the Census makes available
Figure 1.2: U.S. PE Target Employment and Revenue as a Percentage of Total Non-Farm Payroll Employment and 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.

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 Appendices A.5 and A.6.

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.

to academic researchers.
Final Sample

The final sample has 9,300 targets and 190,000 establishments.\textsuperscript{14} Table 1.1 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.

\textsuperscript{14}This number corresponds to PE targets for which I can construct the control group. More detail in Section 1.3.1.
<table>
<thead>
<tr>
<th>Panel A: All Targets</th>
<th>Count (1)</th>
<th>Mean (2)</th>
<th>Median (3)</th>
<th>Std Dev (4)</th>
<th>25th Pct (5)</th>
<th>75th Pct (6)</th>
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</thead>
<tbody>
<tr>
<td>Employment</td>
<td>9,300</td>
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<td>11,000</td>
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<td>4,712,000</td>
<td>4,900</td>
<td>88,500</td>
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<td>6,700</td>
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<td>235.7</td>
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<table>
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<th>Panel B: By LP Category</th>
<th>Count (1)</th>
<th>Mean (2)</th>
<th>Median (3)</th>
<th>Std Dev (4)</th>
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<th>75th Pct (6)</th>
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<td>6,100</td>
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<td>1,108,000</td>
<td>45,500</td>
<td>6,071,000</td>
<td>7,100</td>
<td>267,000</td>
</tr>
<tr>
<td>Revenue/Employment (000s)</td>
<td>1,400</td>
<td>454.9</td>
<td>252.5</td>
<td>2,534</td>
<td>142.1</td>
<td>446.7</td>
</tr>
<tr>
<td>Other Investors</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>1,300</td>
<td>1,500</td>
<td>75</td>
<td>9,200</td>
<td>21</td>
<td>325</td>
</tr>
<tr>
<td>Revenue (000s)</td>
<td>1,300</td>
<td>569,000</td>
<td>19,500</td>
<td>4,902,000</td>
<td>5,100</td>
<td>79,500</td>
</tr>
<tr>
<td>Revenue/Employment (000s)</td>
<td>1,300</td>
<td>399.6</td>
<td>239.8</td>
<td>612.3</td>
<td>141.8</td>
<td>427.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: By GP Category</th>
<th>Count (1)</th>
<th>Mean (2)</th>
<th>Median (3)</th>
<th>Std Dev (4)</th>
<th>25th Pct (5)</th>
<th>75th Pct (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bottom 25th Percentile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>700</td>
<td>1,000</td>
<td>74</td>
<td>4,800</td>
<td>26</td>
<td>287</td>
</tr>
<tr>
<td>Revenue (000s)</td>
<td>700</td>
<td>385,000</td>
<td>19,000</td>
<td>2,396,000</td>
<td>6,000</td>
<td>63,000</td>
</tr>
<tr>
<td>Revenue/Employment (000s)</td>
<td>700</td>
<td>391.0</td>
<td>236.3</td>
<td>616.2</td>
<td>132.9</td>
<td>438.6</td>
</tr>
<tr>
<td>Top 75th Percentile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td>4,800</td>
<td>1,900</td>
<td>80</td>
<td>11,500</td>
<td>21</td>
<td>424</td>
</tr>
<tr>
<td>Revenue (000s)</td>
<td>4,800</td>
<td>653,000</td>
<td>20,500</td>
<td>5,255,000</td>
<td>4,800</td>
<td>104,000</td>
</tr>
<tr>
<td>Revenue/Employment (000s)</td>
<td>4,800</td>
<td>407.6</td>
<td>240.2</td>
<td>1,443</td>
<td>141.8</td>
<td>421.9</td>
</tr>
</tbody>
</table>

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.
1.2.2 Institutional Background

Private equity as a form of financial intermediation has gained prominence over the past 20 years. Figure 1.31 shows the number of PE funds established has risen from less than 30 in 1990 to over 150 in 2018.

Figure 1.3 depicts a schematic institutional structure. Capital flows from institutional investors, also called limited partners or “LPs” (left) to firms or “targets” (right). Institutional investors like public pension funds, insurance companies, sovereign wealth funds, private pensions, endowments, family offices, etc. are suppliers of capital. The intermediary sector consists of agents providing financing to firms. A firm (for e.g., Hilton) generally faces a menu of options to obtain financing: traditional banks, private equity funds (sometimes also referred as non-banks), corporate bonds, public equities, and internal financing. The focus of this paper is the PE fund family or general partner (“GP”, for e.g. Blackstone Group), and its constituent funds (for e.g. Blackstone Capital Partners VI).

Figure 1.3: Connection between Pension Funds, Private Equity Funds, and Target Firms

Notes: The 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.

1.3 Productivity Effects of Private Equity Buyouts

In Section 1.3.1, I discuss the empirical specification, comparing firm outcomes in PE targets post buyout relative to the control group. Section 1.3.2 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.

1.3.1 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.\footnote{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.}

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.\footnote{To give an idea, 1500 GB with 32 CPUs and parallel processing is not sufficient to estimate coefficients of these regressions.} 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.\footnote{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.1.5).} 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, 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 $X_{it} = 0.5 \times (E_{it-1} + E_{it})$. The Davis, Haltiwanger, and Schuh (1996) (“DHS”) growth rate is calculated as $g_{it} = (E_{it} - E_{it-1})/(X_{it})$. $g_{it}$ 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\footnote{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).}, 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.1.1.

Figure 1.4 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 1.19 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.\(^\text{19}\)

\[ y_{it} = \alpha_i + \sum_{j=-5, j \neq -1}^{j=5} \gamma_j (\text{PE}_i \times \text{Buyout Year}_{i(t_0+j)}) + \sum_c \theta_c D_{cit} + \lambda_0 \text{L Firm}_i + \varepsilon_{it} \quad (1.1) \]

\(\text{PE}_i\) takes the value of 1 for firms bought by private equity, and 0 for the controls. \(\text{Buyout Year}_{i,t_0+j}\) is a dummy for each \(j\) taking a value of 1 in the year \(t_0 + j\) relative to buyout year, with \(j = -5, \cdots, 5\). The coefficient of interest is \(\gamma_j\) which measures the effect of PE buyouts on targets relative to control firms in each of the 5 years pre- and post-buyout. As a standard practice, the

\(^{19}\)Prior literature (see Davis et al. (2014) Online Appendix) find a similar pattern of employment growth rates for target and control firms.
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 $t_0 - 1$, $L\text{FIRM}_i$. My difference in differences design does not suffer from bias as in settings of staggered treatments argued in recent papers (Goodman-Bacon (2021); Sun and Abraham (2021); Athey and Imbens (2022); Borusyak, Jaravel, and Spiess (2021); Chaisemartin and D'Haultfoeuille (2020)) 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 1.5 tracks coefficients $\gamma_j$ 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 significantly 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 tightly matched setting. Figure 1.20 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 1.2 shows the long run effects of PE buyouts on targets relative to control firms, i.e., $\gamma$ in the difference in difference specification (1.1) without tracking dynamic effects. Instead of $\text{Buyout \ Year}_{it0+j}$, I have $\text{Post}_{it}$ which takes the value 1 for all years post buyout. I find a $-2.7\%$
Figure 1.5: Difference in Difference Estimated Coefficients $\gamma_j$ Over Time Relative to Buyout Year, PE Deals 1997-2018

Notes: The figure plots difference in difference coefficients $\gamma_j$ from equation (1.1) 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.

The yearly change in employment, −3.0% in revenue, and −0.3% in labor productivity post buyout.\textsuperscript{20} Further, total wages decreases by 2.6%, which implies that total revenue minus 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.

Figure 1.22 Panel A shows labor productivity growth rate difference in difference coefficients $\gamma$ 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

\textsuperscript{20}Appendix A.1.5 (Table A.4) 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).
Table 1.2: Difference in Difference - Long Run Effects of PE Buyouts on Target Relative to Control Firms, PE Deals 1997-2018

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

Notes: The table displays coefficients $\gamma$ of the difference in difference specification:

$$y_{it} = \alpha_t + \gamma (PE_t \times Post_{it}) + \sum_c \theta_c D_{c;it} + \lambda_0 LFIRM_i + \varepsilon_{it}$$

$D_{c;it}$ 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^*p < 0.10$.

-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 1.23 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.1.3. I find a $-29.5%$ five year change post buyout, larger than the $-23.8%$ change for PE deals in 1997 to 2018.

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 produc-
tion function. Establishment $e$’s real gross output at time $t$, $Y_{et}$ can be written as a function of labor $L_{et}$, capital $K_{et}$, and materials $M_{et}$: $Y_{et} = A_{et} \cdot F(K_{et}, L_{et}, M_{et})$. $A_{et}$ represents the plant level productivity (TFP). Following Baily, Hulten, and Campbell (1992), $\ln TFP_{et}$, the log of total factor productivity at the plant level is written as,

$$\ln TFP_{et} = \ln Y_{et} - \alpha_K \ln K_{et} - \alpha_L \ln L_{et} - \alpha_M \ln M_{et} \quad (1.2)$$

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 A.2.2 shows the results, and Appendix A.7.1 details construction of variables.

Figure 1.6: Cumulative Changes of Outcome Variables for Manufacturing Target Relative to Control Firms Over Time, PE Deals 1997-2018

![Figure 1.6](image_url)

**Notes:** The figure cumulates difference in difference estimated coefficients $\gamma_j$ from specification (1.1) for manufacturing firms over time relative to buyout year.

Figure 1.6 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.

Subsample Analysis

There is considerable variation in labor productivity effects post buyout at target firms across time periods. Figure 1.7 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 periods. Figure 1.7 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.
Figure 1.7: 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.
1.3.2 Event Study around PE Buyout

Next, I focus only on target firms to study post buyout effects.\(^{21}\) This specification will form the baseline for the LP and GP heterogeneity analysis going forward.

\[
y_{it} = \alpha_i + \alpha_0 \text{Post Buyout}_{it} + \gamma \text{LFIRM}_i + \text{Fixed Effects} + \epsilon_{it} \tag{1.3}
\]

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. \(\alpha_0\) is the coefficient of interest measuring the effects of outcome variables post buyout activity. Year fixed effects are included in all specifications.

Table 1.3 shows estimated coefficients \(\alpha_0\) for equation (1.3) 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 year, revenue by \(-8.6\%\), with an insignificant \(-0.2\%\) change in labor productivity. Figure 1.24 shows the dynamic estimates five years pre- and post-buyout.\(^{22}\)

1.4 Public Pensions Capital Commitment Over Time

Figure 1.14 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 1.8 shows the three year moving average of capital commitment shares by the most underfunded pension tercile. The blue line shows that the most underfunded pensions contributed

\(^{21}\)This specification captures the pre-post “diff” in the difference in difference specification.

\(^{22}\)Additional robustness checks (not reported) include specifications with year and industry fixed effects; year and firm size fixed effects; year and firm age fixed effects; year and type of unit fixed effects; year, industry and firm size fixed effects; industry \(\times\) year, firm size, age, and type fixed effects. Results remain unchanged.
Table 1.3: Event Study Estimated Coefficients of Post Buyout, PE Deals 1997-2018

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Emp $g$</th>
<th>Pay $g$</th>
<th>Rev $g$</th>
<th>Rev $g$ -Emp $g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post Buyout</td>
<td>-0.084***</td>
<td>-0.075***</td>
<td>-0.086***</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.011)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Firm Size FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Firm Age FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Industry FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Type of Unit FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Lagged Firm g</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Weighted Emp $t_0$</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>70,000</td>
<td>70,000</td>
<td>70,000</td>
<td>70,000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.183</td>
<td>0.193</td>
<td>0.132</td>
<td>0.015</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.023</td>
<td>0.028</td>
<td>0.026</td>
<td>0.003</td>
</tr>
</tbody>
</table>

Notes: The table displays coefficients $\alpha_0$ of the event study specification (1.3):

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

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

Figure 1.8: 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.
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 1.3.1. Specifically, substantial increases are seen post 2010, the period after 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.

1.5 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 A.3.1 follows an approach similar to Abowd, Kramarz, and Margolis (1999), and adds LP and GP identity interactions with Post Buyout in specification (1.3). 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 sovereign 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 infor-
mation 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,

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

(1.4)

I split $\phi_i$ into terciles to estimate the following specification.

$$
y_{it} = \alpha_t + \alpha_0 \text{Post}_{it} + \sum_{r=1}^{3} \beta^r \left( \text{Post}_{it} \times I_t^{U/F^r} \right) + \gamma \text{LFIRM}_t + \text{Fixed Effects} + \epsilon_{it}
$$

(1.5)

where $I_t^{U/F^r}$ 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 1.9 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 1.9: Estimates of Post Buyout $\times$ 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 (1.5) with two categories: other investors and public pension funds supported firms. Panel B plots coefficients from four categories in equation (1.5): other investors, most underfunded, medium underfunded, and least underfunded public pension supported firms. Bars represent 90% confidence intervals.

Tables 1.9 and 1.10 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 A.15 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. To account for macroeconomic conditions, I residualize underfunded ratios with local region fixed effects and 10 year interest rates, and find similar results (Figure A.14).

Figure 1.10 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 1.10: Labor Productivity 
Dynamic Estimates for Post Buyout × Investor Type Over Time Relative to Buyout Year, PE Deals 1997-2018

Notes: Figure plots coefficients $\beta_i$, $i = -3, \cdots, 3$ for the dynamic version of equation (1.5) for three years before and after buyout for the most underfunded and other investor category of firms. Connected lines represent 90% confidence intervals.

23 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 A.13, Table 1.11).
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 characteristics 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 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, 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 (1.5) with varying splits of firms based on GP quality distribution. Figure 1.11 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

---

24 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.
changes. Figure 1.25 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 GP qualities, can capture both causality
and selection into investment projects.

Figure 1.11: Labor Productivity g Estimates of Post Buyout × GP Quality Percentile, PE Deals
1997-2018

\[ y_{it} = \alpha_i + \alpha_0 Post_{it} + \beta \left( Post \times 1_{Bot} \right) + \gamma LFINM_i + \xi_i + \epsilon_{it} \]  \hspace{1cm} (1.6)

where 1_{Bot} is a dummy which is 1 for targets supported by GP quality in bottom xth percentile. Post_{it} captures the
effect on targets financed by (1-x)th percentile of GP quality distribution. Each color shows estimates from a different
regression, capturing targets financed by different splits of GP quality. 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.

1.6 Mechanism and Discussion

1.6.1 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. 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 1.12 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%

25Supported by interviews with industry professionals and Preqin data provider.
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 1.12: Percent of Investment Linkages Between Most Underfunded Pensions and GPs Across Time

Notes: This figure counts connections of investment 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 for lower quality GPs. 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

---

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

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

(1.7)

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.\(^{27}\) 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 (1.7).

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 \( \gamma_t \) 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 1.4 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 point change corresponds to a \(-10.3\%\) change.\(^{28}\) The 10.3\% decrease in size of the PE fund for a one-standard-deviation increase in

\(^{27}\)Details of the measure defined in Section A.4.1.

\(^{28}\)Average logarithmic size is 8.89 (≡ $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 (≡ $6,525 mn.). In level terms, the change in size of the fund is -$749 mn., which is a -10.3% change.
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 1.12). 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.

### 1.6.2 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 specification (1.7) with $y_{p,t}$ 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, but not for GP as these regressions are solely at the pension fund-year level. The regressions

<table>
<thead>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
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<td>-0.614***</td>
<td>-0.534***</td>
<td>-0.616***</td>
</tr>
<tr>
<td></td>
<td>(0.176)</td>
<td>(0.181)</td>
<td>(0.193)</td>
<td>(0.198)</td>
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<tr>
<td>LP AUM</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Past Asset Allocations</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Benchmark Returns</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Industry Focus</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Strategy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Region Focus</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Domicile</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Vintage Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Positive PE Allocation</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Regression Type</td>
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<td>OLS</td>
<td>OLS</td>
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<td>Observations</td>
<td>1455</td>
<td>1244</td>
<td>1084</td>
<td>850</td>
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<tr>
<td>Adjusted R squared</td>
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<td>0.311</td>
<td>0.280</td>
<td>0.461</td>
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<td>Dependent Variable Mean</td>
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<td>8.695</td>
<td>8.828</td>
<td>8.896</td>
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<td>Dependent Variable Std</td>
<td>1.209</td>
<td>1.202</td>
<td>1.116</td>
<td>1.121</td>
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</tbody>
</table>

*Notes: Standard errors in parentheses.

$^* p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$
estimate the effect of pensions’ underfunded positions on its total PE realized returns. Table 1.5 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 1.5: Correlation Between Public Pensions Underfunded Positions and PE Returns, 2001-2021

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

Notes: 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.
1.7 Identifying Desperate Capital Using Public Unions

1.7.1 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 1.26). 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,

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

There is a wide cross-sectional variation in public unionization rates across states. Figure 1.28 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.\textsuperscript{29} Freeman (1983) shows unions increase pension coverage. Figure 1.29 shows evidence of a $+17.3\%$ significant correlation between underfunded public pensions and one year lagged public union density for 2011 to 2018.\textsuperscript{30}

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.

\subsection*{1.7.2 Empirical Methodology and Results}

Formally, the first and second stage of the empirical specification are shown in equations (1.9) and (1.10) respectively.

\begin{align*}
\text{Underfunded Ratio}_{ps\!t} &= \alpha_t + \beta \cdot \text{Union Density } (\%)_{st-1} + \text{Controls} + \epsilon_{p\!s\!t} \quad (1.9) \\
\gamma_{ps\!t|p\in j} &= \gamma_t + \beta_{IV} \cdot \text{Underfunded Ratio}_{p\!s\!t} + \text{Controls} + \epsilon_{p\!s\!t} \quad (1.10)
\end{align*}

As before, $p$ stands for pension fund, $s$ is state, $j$ is GP, and $t$ is year. $y_{ps\!t|p\in j}$ is the size of GP a public pension commits capital to in time $t$. $y_{ps\!t}$ 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.

\textsuperscript{29}For instance, the link https://uniontrack.com/blog/unions-retirement-benefits mentions ways unions impact pensions.

\textsuperscript{30}Correlation is $+6.3\%$ and significant for 1997-2018.
Table 1.6 reproduces the OLS from column (4) in Tables 1.4 and 1.5, and presents the first and second stage IV results. The first three columns correspond to \textit{GP Quality}, and the last three show results for \textit{Realized PE Returns}. The first stage coefficient of interest is $\beta$, and expected to be positive. For GP Quality for instance, the coefficient on \textit{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.

Table 1.6: Instrumental Variable Results for GP Quality and Realized PE Returns

<table>
<thead>
<tr>
<th>GP Quality</th>
<th>Realized PE Returns</th>
</tr>
</thead>
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<td>(1) Underfunded Ratio</td>
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<tr>
<td>Lag 1 Year Union Density</td>
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<td></td>
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<tr>
<td>Assets</td>
<td>Yes</td>
</tr>
<tr>
<td>Average Past Asset Allocations</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Benchmark Returns</td>
<td>Yes</td>
</tr>
<tr>
<td>Investment Consultant Dummies</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Industry Focus Dummies</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Strategy Dummies</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Region Focus Dummies</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Domicile Dummies</td>
<td>Yes</td>
</tr>
<tr>
<td>Vintage Year FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Pension Fund FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Positive PE Allocation</td>
<td>Yes</td>
</tr>
<tr>
<td>Regression Type</td>
<td>First Stage</td>
</tr>
<tr>
<td>Observations</td>
<td>850</td>
</tr>
<tr>
<td>Adjusted R Squared</td>
<td>0.243</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.231</td>
</tr>
<tr>
<td>Dependent Variable Std</td>
<td>0.175</td>
</tr>
</tbody>
</table>

Notes: Columns (1)-(3) present results for GP Quality from specifications (1.9), (1.7), and (1.10). 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.

It is important for the IV to be “strong”, i.e., the exogenous variable – one year lagged public union density to be strongly correlated with the endogenous variable – underfunded positions of public pensions, especially for IV estimation in finite samples. In column (1), the $F$ statistic for the null that $\beta = 0$ is 29.6, which is greater than the rule of thumb ($F \geq 10$) proposed by Staiger.
and Stock (1997), and the 10% critical value in Table 5.2 of Stock and Yogo (2005). Similarly, in column (4), the $F$ statistic is 24.1 ($t = 4.91$), which satisfies 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., desperate 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 further substantiate the cause for underfunded positions, I estimate specification (1.5) by splitting targets into terciles of state public union density of the corresponding public pensions supporting the target. Column (1) of Table 1.7 reproduces estimates from equation (1.5), 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 $-7.0\%$.

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.
### Table 1.7: Post Buyout Labor Productivity Effects by Investor Split Using Union Density

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

**Notes:** The table displays coefficients $a_0$ and $\beta$ from specification (1.5). 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 1.10 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: $*** p < 0.01$, $** p < 0.05$, $* p < 0.10$.

## 1.8 Economic and Policy Implications

### 1.8.1 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 1.8 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 1.10 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.

Table 1.8: Economic Loss and Gain by Investor Between Year -1 and +3 Relative To Buyout

<table>
<thead>
<tr>
<th>Panel A: Targets Vs. Controls in Raw Data</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Employment</td>
<td>Revenue</td>
<td>Revenue Per Employee</td>
</tr>
<tr>
<td></td>
<td>(000s)</td>
<td>(%)</td>
<td>($$ Bn.)</td>
</tr>
<tr>
<td>All Targets</td>
<td>-1,500</td>
<td>-25.6</td>
<td>-670</td>
</tr>
<tr>
<td>Controls</td>
<td>+0.3</td>
<td>+2.6</td>
<td></td>
</tr>
</tbody>
</table>

| 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 (1.5). Revenue is deflated by the U.S. GDP Price Deflator Series, and is expressed in 2020 U.S. dollars.
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.

1.8.2 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 lump-sum 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
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.

1.9 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.
1.10 Additional Figures and Tables

Figure 1.13: 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 1.14: Portfolio Allocation of U.S. Public Pensions Over Time

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/).

Notes: The y axis represents portfolio allocation of assets as a percentage of total assets.
Figure 1.15: Visualization of Data and its Sources

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 1.17: 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 1.18: 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 1.19: 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 1.20: Difference in Difference Estimated Coefficients $\gamma_j$ for Two Year Continuing Firms, PE Deals 1997-2018

(A) Employment $g$

(B) Revenue $g$

(C) Rev $g$ - Emp $g$

(D) Long Run Effects

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Emp $g$</th>
<th>Rev $g$</th>
<th>Rev $g$-Emp $g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment $\times$ Post Buyout</td>
<td>-0.0261***</td>
<td>-0.0266***</td>
<td>-0.0005</td>
</tr>
<tr>
<td>Industry $\times$ Age $\times$ Size $\times$ Type $\times$ Transaction Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Lagged Firm $g$</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Weighted Emp $t_0$</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>14,830,000</td>
<td>14,830,000</td>
<td>14,830,000</td>
</tr>
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<td>Adjusted $R^2$</td>
<td>0.0394</td>
<td>0.0405</td>
<td>0.0092</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0088</td>
<td>0.0155</td>
<td>0.0067</td>
</tr>
</tbody>
</table>

Notes: Panels A-C show difference in difference coefficients $\gamma_j$ from equation (1.1). Table in Panel D displays coefficients $\gamma$ of the difference in difference specification:

$$y_{it} = \alpha_t + \gamma(PE_t \times Post_{it}) + \sum_c \theta_c D_{cit} + \lambda_0LFIRM_i + \epsilon_{it}$$

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

57
Figure 1.21: 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 1.20 Panels A-C. The coefficients are normalized to 0 in year -1 relative to buyout.
Notes: This figure plots estimated labor productivity coefficients $\gamma$ of the difference in difference specification:

$$y_{it} = \alpha_t + \gamma(PE_{i} \times \text{Post}_{it}) + \sum_c \theta_c D_{c_{it}} + \lambda_0 L_{\text{FIRM}_i} + \varepsilon_{it}$$

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

Notes: This figure plots estimated labor productivity coefficients $\gamma$ of the difference in difference specification:

$$y_{it} = \alpha_t + \gamma(\text{PE}_t \times \text{Post}_it) + \sum_c \theta_c D_{c_{it}} + \lambda_0 \text{FIRM}_i + \varepsilon_{it}$$

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 1.24: 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:

$$y_{it} = \alpha_t + \sum_{t=t_0+5}^{t_0-5, t \neq t_0-1} \alpha_{0,t} \text{Buyout}_{it} + \gamma \text{LFIRM}_{i} + \text{Fixed Effects} + \epsilon_{it}$$  \hspace{1cm} (1.11)

$\text{Buyout}_{it}$ 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. $\text{LFIRM}_{i}$ 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 1.9: Estimated Coefficients for Post Buyout by Investor Identity, PE Deals 1997-2018

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

Notes: The table displays coefficients $a_0$ and $\beta^*$ from specification (1.5). 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 1.10: Estimated Coefficients for Post Buyout by Investor Type and Public Pension Fund Ratio, PE Deals 1997-2018

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Emp g (1)</th>
<th>Rev g (2)</th>
<th>Rev g-Emp g (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Investor Split</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post Buyout (Base: Other Investors)</td>
<td>(-0.1270^{***})</td>
<td>(-0.0748^{***})</td>
<td>(0.0522^*)</td>
</tr>
<tr>
<td>Post Buyout × Most Underfunded Pensions</td>
<td>(0.0526^*)</td>
<td>(-0.0517^{***})</td>
<td>(-0.1040^{***})</td>
</tr>
<tr>
<td>Post Buyout × Medium Underfunded Pensions</td>
<td>(0.0334)</td>
<td>(-0.0132)</td>
<td>(-0.0466)</td>
</tr>
<tr>
<td>Post Buyout × Least Underfunded Pensions</td>
<td>(0.0528^*)</td>
<td>(-0.0032)</td>
<td>(-0.0559^{**})</td>
</tr>
<tr>
<td>Observations</td>
<td>53,500</td>
<td>53,500</td>
<td>53,500</td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>0.1920</td>
<td>0.1450</td>
<td>0.0203</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0249</td>
<td>0.0252</td>
<td>0.0003</td>
</tr>
<tr>
<td><strong>Panel B: All</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post Buyout</td>
<td>(-0.0874^{***})</td>
<td>(-0.0845^{***})</td>
<td>(0.0029)</td>
</tr>
<tr>
<td>Observations</td>
<td>53,500</td>
<td>53,500</td>
<td>53,500</td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>0.1900</td>
<td>0.1440</td>
<td>0.0165</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0249</td>
<td>0.0252</td>
<td>0.0003</td>
</tr>
</tbody>
</table>

| 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 \(a_0\) and \(\beta\) from specification (1.5). 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 1.11: Estimated Coefficients for Post Buyout by Pension Fund Underfunded Ratio, PE Deals 1997-2018

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Emp g</th>
<th>Rev g</th>
<th>Rev g-Emp g</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>Panel A: Pension Funded Ratio Split</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post Buyout (Base: Least Underfunded)</td>
<td>0.0570***</td>
<td>0.0700***</td>
<td>0.0130</td>
</tr>
<tr>
<td></td>
<td>(0.0143)</td>
<td>(0.0126)</td>
<td>(0.0129)</td>
</tr>
<tr>
<td>Post Buyout × Most Underfunded</td>
<td>0.0099</td>
<td>0.0519***</td>
<td>0.0420**</td>
</tr>
<tr>
<td></td>
<td>(0.0140)</td>
<td>(0.0200)</td>
<td>(0.0188)</td>
</tr>
<tr>
<td>Post Buyout × Medium Underfunded</td>
<td>0.0099</td>
<td>0.0047</td>
<td>0.0146</td>
</tr>
<tr>
<td></td>
<td>(0.0159)</td>
<td>(0.0161)</td>
<td>(0.0156)</td>
</tr>
<tr>
<td>Observations</td>
<td>44,500</td>
<td>44,500</td>
<td>44,500</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.2020</td>
<td>0.1460</td>
<td>0.0197</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0237</td>
<td>0.0223</td>
<td>-0.0014</td>
</tr>
<tr>
<td><strong>Panel B: All</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post Buyout</td>
<td>0.0601***</td>
<td>0.0772***</td>
<td>0.0171</td>
</tr>
<tr>
<td></td>
<td>(0.0125)</td>
<td>(0.0117)</td>
<td>(0.0116)</td>
</tr>
<tr>
<td>Observations</td>
<td>44,500</td>
<td>44,500</td>
<td>44,500</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.2020</td>
<td>0.1440</td>
<td>0.0185</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0237</td>
<td>0.0223</td>
<td>-0.0014</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Year FE</th>
<th>Firm Size FE</th>
<th>Firm Age FE</th>
<th>Industry FE</th>
<th>Type of Unit FE</th>
<th>Lagged Firm g</th>
<th>Weighted Emp $t_0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Pension Funded Ratio Split</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel B: All</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The table displays coefficients $a_0$ and $\beta^*$ from specification (1.5). 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 1.25: Estimates of Post Buyout × GP Quality Percentile, PE Deals 1997-2018

Notes: The figure shows estimates $\beta$ from the specification:

$$y_{it} = \alpha_t + \alpha_0 \text{Post}_{it} + \beta \left( \text{Post} \times \gamma_{\text{Bot}x} \right) + \gamma_{\text{FIRM}} + \varepsilon_{it}$$

where $\gamma_{\text{Bot}x}$ is a dummy which is 1 for targets supported by GP quality in bottom $x$th percentile. $\text{Post}_{it}$ captures the effect on targets financed by $(1-x)th$ percentile of GP quality distribution. Each color shows estimates from a different regression, capturing targets financed by different splits of GP quality. Bars represent 90% confidence intervals. Panel A corresponds to employment growth rates, and Panel B for revenue growth rates. Bars represent 90% confidence intervals.
Figure 1.26: 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 1.27: 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 1.28: 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 1.29: 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 1.30: Private Equity and Private Debt Allocations for U.S. Public Pension Funds with AUM above $50 mn as of December 2020

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

<table>
<thead>
<tr>
<th>Pension Fund</th>
<th>AUM (USD Bn.)</th>
<th>PE Target Allocation (USD Bn.)</th>
<th>PE Allocation (USD Bn.)</th>
<th>PE Allocation (%)</th>
<th>PD Target Allocation (USD Bn.)</th>
<th>PD Allocation (USD Bn.)</th>
<th>PD Allocation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CalPERS - California Public Employees’ Retirement System</td>
<td>403.00</td>
<td>33.34</td>
<td>27.59</td>
<td>6.62</td>
<td>2.14</td>
<td>0.53</td>
<td>0.33</td>
</tr>
<tr>
<td>California State Teachers’ Retirement System (CalSTRS)</td>
<td>275.01</td>
<td>25.79</td>
<td>26.02</td>
<td>10.09</td>
<td>0.66</td>
<td>0.24</td>
<td></td>
</tr>
<tr>
<td>New York State Common Retirement Fund</td>
<td>226.40</td>
<td>22.64</td>
<td>22.64</td>
<td>10.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Florida State Board of Administration</td>
<td>213.50</td>
<td>12.47</td>
<td>15.17</td>
<td>7.30</td>
<td>8.54</td>
<td>3.05</td>
<td>1.43</td>
</tr>
<tr>
<td>Teacher Retirement System of Texas</td>
<td>162.66</td>
<td>21.73</td>
<td>21.75</td>
<td>14.01</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regents of the University of California</td>
<td>118.80</td>
<td>8.91</td>
<td>6.40</td>
<td>5.39</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New York State Teachers’ Retirement System</td>
<td>118.76</td>
<td>9.64</td>
<td>9.40</td>
<td>7.80</td>
<td>1.19</td>
<td>0.70</td>
<td>0.59</td>
</tr>
<tr>
<td>Washington State Investment Board</td>
<td>116.98</td>
<td>27.45</td>
<td>25.10</td>
<td>21.03</td>
<td>1.22</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td>State of Wisconsin Investment Board</td>
<td>116.30</td>
<td>12.99</td>
<td>8.76</td>
<td>7.42</td>
<td>0.51</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td>North Carolina Department of State Treasurer</td>
<td>107.50</td>
<td>6.44</td>
<td>5.51</td>
<td>5.13</td>
<td>1.94</td>
<td>2.15</td>
<td>2.00</td>
</tr>
<tr>
<td>Ohio Public Employees’ Retirement System</td>
<td>106.30</td>
<td>11.15</td>
<td>10.74</td>
<td>10.52</td>
<td></td>
<td>1.69</td>
<td>1.61</td>
</tr>
<tr>
<td>Minnesota State Board of Investment</td>
<td>105.15</td>
<td>6.57</td>
<td>6.42</td>
<td></td>
<td></td>
<td>1.69</td>
<td>1.61</td>
</tr>
<tr>
<td>Virginia Retirement System</td>
<td>94.00</td>
<td>12.25</td>
<td>11.60</td>
<td>12.31</td>
<td>14.10</td>
<td>13.44</td>
<td>14.30</td>
</tr>
<tr>
<td>Teachers’ Retirement System of the City of New York</td>
<td>87.05</td>
<td>4.70</td>
<td>4.72</td>
<td>5.43</td>
<td></td>
<td>8.04</td>
<td>9.24</td>
</tr>
<tr>
<td>Oregon State Treasury</td>
<td>83.91</td>
<td>14.69</td>
<td>18.34</td>
<td>21.85</td>
<td>4.32</td>
<td>5.15</td>
<td></td>
</tr>
<tr>
<td>NJ Division of Investment</td>
<td>80.20</td>
<td>10.44</td>
<td>8.88</td>
<td>11.06</td>
<td>6.42</td>
<td>1.44</td>
<td>1.79</td>
</tr>
<tr>
<td>State Teachers’ Retirement System of Ohio</td>
<td>78.72</td>
<td>5.61</td>
<td>7.68</td>
<td>9.99</td>
<td></td>
<td>8.04</td>
<td>9.24</td>
</tr>
<tr>
<td>Massachusetts Pension Reserves Investment Management Board</td>
<td>78.72</td>
<td>9.60</td>
<td>8.16</td>
<td>10.88</td>
<td>3.15</td>
<td>1.47</td>
<td>1.87</td>
</tr>
<tr>
<td>Michigan Department of Treasury</td>
<td>76.42</td>
<td>13.99</td>
<td>14.06</td>
<td>19.47</td>
<td>2.41</td>
<td>3.16</td>
<td></td>
</tr>
<tr>
<td>New York City Employees’ Retirement System</td>
<td>72.61</td>
<td>5.89</td>
<td>5.13</td>
<td>6.96</td>
<td>6.35</td>
<td>8.75</td>
<td></td>
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<tr>
<td>Los Angeles County Employees’ Retirement Association</td>
<td>60.73</td>
<td>6.07</td>
<td>6.98</td>
<td>11.49</td>
<td>1.82</td>
<td>1.72</td>
<td></td>
</tr>
<tr>
<td>Pennsylvania Public School Employees’ Retirement System</td>
<td>58.00</td>
<td>8.70</td>
<td>9.19</td>
<td>15.84</td>
<td>1.00</td>
<td>1.72</td>
<td></td>
</tr>
<tr>
<td>Maryland State Retirement and Pension System</td>
<td>58.00</td>
<td>7.54</td>
<td>8.24</td>
<td>14.20</td>
<td>1.22</td>
<td>2.11</td>
<td></td>
</tr>
<tr>
<td>Teachers’ Retirement System of the State of Illinois</td>
<td>55.72</td>
<td>8.04</td>
<td>6.14</td>
<td>11.46</td>
<td>3.34</td>
<td>3.95</td>
<td>7.38</td>
</tr>
<tr>
<td>Tennessee Consolidated Retirement System</td>
<td>53.55</td>
<td>4.82</td>
<td>3.98</td>
<td>7.44</td>
<td>3.75</td>
<td>3.95</td>
<td>7.38</td>
</tr>
<tr>
<td>Colorado Public Employees’ Retirement Association</td>
<td>53.02</td>
<td>4.30</td>
<td>3.79</td>
<td>7.50</td>
<td>0.27</td>
<td>0.51</td>
<td></td>
</tr>
</tbody>
</table>

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 Prequin.
Figure 1.31: 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.
Chapter 2: Flattening the Curve: Pandemic-Induced Revaluation of Urban Real Estate

We show that the COVID-19 pandemic brought house price and rent declines in city centers, and price and rent increases away from the center, thereby flattening the bid-rent curve in most U.S. metropolitan areas. Across MSAs, the flattening of the bid-rent curve is larger when working from home is more prevalent, housing markets are more regulated, and supply is less elastic. Housing markets predict an urban revival with urban rent growth exceeding suburban rent growth for the foreseeable future, as working from home recedes.

2.1 Introduction

Cities have historically been a major source of growth, development, and knowledge spillovers (Glaeser (2011)). In developing and developed countries alike, rising urbanization rates (United Nations (2019)) have led to increased demand for real estate in city centers and contributed to problems of housing affordability (Favilukis, Mabille, and Van Nieuwerburgh (2019)), especially in superstar cities (Gyourko, Mayer, and Sinai (2013)). The inelasticity of housing supply in urban centers means that a large fraction of economic growth in the last few decades has accrued to property owners, rather than improving the disposable income of local workers (Hornbeck and Moretti (2018); Hsieh and Moretti (2019)).

This long-standing pattern reversed in 2020 as the COVID-19 pandemic led many residents to

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1This chapter is based on Gupta et al. (2021). The paper is published in the Journal of Financial Economics and is the Editor’s Choice Article for November 2022. Toni M. Whited was the editor for this article. This paper is also part of the NBER Working Paper Series (#WP 28675). The study is cited in multiple news reports, such as The Economist, The New York Times, VoxEU CEPR, among others. We thank Zillow, Apartment List Rent Data, VenPath, Realtor, Infutor, Pulsenomics, and Safegraph for providing data. We thank Joshua Coven, Ki Lee, and Luofeng Zhou for excellent research assistance, and Igor Popov from Apartment List and Joshua Clark from Zillow for helpful conversations. The authors have no conflicts of interest to declare.
flee city centers in search of safer ground away from urban density. This urban flight was greatly facilitated by the ability, indeed the necessity, to work from home. Downtown office use hit historic lows in 2020 and remains low well into 2021, possibly turning many temporary suburbanites into permanent ones.² We document this migration pattern and show that it had a large impact on the demand for suburban relative to urban residential real estate.

An important question is whether real estate markets will return to their pre-pandemic state or be changed forever. There is much uncertainty circling around this question. Existing survey evidence indicates an increased willingness by employers to let employees work from home and an increasing desire from employees to do so, but without much evidence on lost productivity.³ In this paper, we argue that by comparing the changes in house prices—which are forward looking—to the changes in rents in city centers and in the suburbs, we can glance an early answer to this difficult question.

We begin by documenting how urban agglomeration trends have shifted in the wake of the COVID-19 pandemic. The central object of interest is the bid-rent function, or the land price gradient, which relates house prices and rents to distance from the city center. Prices and rents in the city center tend to be higher than in the suburbs, with the premium reflecting the scarcity of land available for development (including due to regulatory barriers), closer proximity to workplaces, urban amenities, and agglomeration effects. While bid-rent functions are typically downward sloping, we document striking changes in the slope of this relationship since the beginning of the COVID-19 pandemic. House prices far from the city center have risen faster than house prices in the center between December 2019 and December 2020. More starkly, rents in the suburbs

² According to JLL, U.S. office occupancy declined by a record 84 million square feet in 2020, propelling the vacancy rate to 17.1% at year-end. In addition, the sublease market grew by 50% in 2020, an increase of 47.6 million square feet (Jones Lang LaSalle (2020)).

³ A survey of company leaders by Gartner found that 80% plan to allow employees to work remotely at least part of the time after the pandemic, and 47% will allow employees to work from home full-time. A PwC survey of 669 CEOs shows that 78% agree that remote collaboration is here to stay for the long-term. In a recent FlexJobs survey, 96% of respondents desire some form of remote work; 65% of respondents report wanting to be full-time remote employees post-pandemic, and 31% want a hybrid remote work environment. Bloom (2020) finds that 42% of the U.S. workforce was working remotely as of May 2020, and Barrero, Bloom, and Davis (2021) estimates that the number of remote working days will increase four-fold in future years to 20%. Harrington and Emanuel (2020) finds positive productivity effects of working from home, consistent with Bloom et al. (2015), but adverse selection into remote work.
rose strongly while rents in the center fell—in some metropolitan areas strongly—in 2020. The negative slope of the bid-rent function has become less negative. In other words, the pandemic has flattened the bid-rent curve.

Figure 2.1 illustrates this changing slope over the course of the pandemic. Each observation is the slope of the bid-rent function for a particular month. The rent gradient is plotted in the left panel, and the price gradient is shown in the right panel. The bid-rent slope coefficients are estimated by pooled panel regression on a sample of all ZIP codes in the largest 30 metropolitan areas in the U.S. for which we have both rent and price data. Distance is measured as the log of one plus the distance in kilometers of the ZIP code’s centroid from the city hall of the main city of the metropolitan area. The elasticity of rents to distance changes from $-0.032$ in December 2019 to $-0.0001$ in December 2020. The slope change for rents ($\Delta \delta = 0.32$) corresponds to suburban rents appreciating by 12.1 percentage points more than in the urban core of the metropolitan area. The rent gradient level estimate in December 2020 indicates that the entire urban rent premium has been eliminated. The evolution of the price gradient is qualitatively similar but quantitatively weaker. The elasticity of house prices to distance changes from $-0.103$ pre-pandemic to $-0.090$ in December 2020. The change in slope for price ($\Delta \delta = 0.012$) means that house prices 50kms from the city center grew by 6.5 percentage points more than house prices close to the city center.

We also find large changes in housing quantities reflecting greater suburban demand. Active listings, a measure of the housing inventory, displays large increases in the urban center and large decreases in the suburbs. A measure of housing liquidity shows that days-on-the-market increase in the urban core and falls sharply in the suburbs. There is a strong negative cross-sectional relationship between the house price change in a ZIP code on the one hand, and the change in inventory and days-on-the-market on the other hand. Since housing supply tends to be more elastic in the suburbs than in the urban core, part of the adjustment to higher demand is accommodated through increases in quantity. While the observed quantity adjustments are arguably limited over the short period since the pandemic took hold, we expect them to be larger in the medium run. Shifting population to areas with higher supply elasticity will have important implications for housing af-
Figure 2.1: Rent and Price Gradients across top 30 MSAs

Notes: This plot shows bid-rent function slope coefficients estimated from the panel regression in equation (2.1): $\ln p_{jt} = \delta_j (\text{Month}_t \times \text{[ln}(1 + D(z'_j, z''_j)]) + \beta X_{jt} + \alpha_t \text{Month}_t + \gamma \text{MSA}_j + \epsilon_{jt}$. The dependent variable is log rent (left panel) and log price (right panel). The graph plots $\delta_j$, the coefficients on the interaction terms of month and distance. The sample consists of all ZIP code-month observations in the largest 30 metropolitan areas for which both price and rent data from Zillow are available. The time series is from January 2018 until December 2020. Distance is measured in kilometers between the centroid of the ZIP code and the city hall of the main city of the metropolitan area. The two panels report the change in gradient from Dec 2019 to Dec 2020 as $\Delta \delta$. The controls $X_{jt}$ are median household income, median age of the head of household, proportion of Black households, and proportion of individuals who make over $150k, all drawn from the 2019 American Community Survey. The specification also includes month and MSA fixed effects. We draw a vertical line to define the post-pandemic period, starting in January 2020.

Next, we link these changes in prices and rents to migration data using high-frequency cellphone location data. ZIP codes close to the center of the metro area lost population while suburban ZIP codes gained people. We show that places that experienced the strongest migration also saw the largest price and rent changes. We also link migration to remote work using the Dingel and Neiman (2020) measure of occupational ability to work from home. This finding suggests that many workers with the capacity to leave cities did so, propelling housing values in suburban areas at the cost of urban ones. We find similar migration patterns based on within-user changes and in address changes using data from Infutor.

To get at the underlying mechanism, we study the cross-sectional variation in the change in the slope of the bid-rent function across MSAs. We find that the changes are larger in MSAs that have (i) a higher presence of jobs that can be done from home, (ii) more stringent pandemic lock-down measures (which result in the loss of urban amenities such as theaters and restaurants),
and (iii) lower housing supply elasticity stemming from higher physical or regulatory barriers to development. The strongest association is with the presence of remote workers, which suggests two important economic forces. Workers with jobs that can be done remotely are able to relocate their home location in the context of changing remote work policies. At the same time, these—largely high-skilled—workers may also change their preferences for urban amenities. We test for the role of changing amenities by controlling for the stringency of pandemic lock-down measures across MSAs, and find that the working-from-home measure remains a strong determinant of the cross-MSA variation in the rent and price gradients.

To further disentangle the effect of working from home on the one hand and COVID-19 stringency measures and urban amenities on the other hand, we turn to a ZIP-code level analysis. A specification with MSA-fixed effects allows us to control for all MSA-specific characteristics, like common amenities. We also account for amenities measured at the ZIP-level. We find that ZIP codes with higher exposure to work-from-home (WFH) see lower house price and rent growth even after accounting for ZIP-level variation in amenities and other ZIP-level socio-economic variables. We interpret the residual association of WFH with real estate outcomes in this specification as largely reflecting the channel of workers re-optimizing location choices in the context of reduced commuting times. Furthermore, we find that WFH associates more strongly with rent changes than with price changes. Since prices are forward-looking, this result is consistent with housing markets anticipating a partial reversal of remote work. Still, the effect on prices suggests that many households expect permanent or at least highly persistent changes in WFH practices.

We develop a present-value model in the tradition of Campbell and Shiller (1988) to study what the relative changes in urban versus suburban house prices and rents teach us about the market’s expectations of future rent growth in urban versus suburban locations. By studying differences between suburban and urban locations, we control for common drivers of house prices such as low interest rates. The much larger decline in rents than in prices in urban ZIP codes, and the equally large increase in prices and rents in the suburbs, imply that the price-rent ratio became more steeply downward sloping in distance from the center. What the relative increase in the urban
price-dividend ratio signifies for future expected rent growth depends on the model’s assumptions about the long run.

If housing markets expect a gradual but full return to the pre-pandemic state, then the increase in the urban-minus-suburban price-rent ratio implies higher expected rent growth in the urban core than in the suburbs for the next several years. Under the assumption that urban-minus-suburban risk premia did not change during the pandemic, the cumulative urban-suburban rent change is 8.1 percentage points for the average MSA. If, instead, urban risk premia rose by 1 percentage point relative to the suburbs during the pandemic, then the expected differential cumulative rent change becomes 15.6 percentage points.

We expect a different outcome, however, in the case where the pandemic has led to permanent changes to housing markets. In this scenario, the change in price-rent ratios implies that urban rents will grow by 0.6 percentage points faster than suburban rents going forward, assuming that risk premia did not change. If urban risk premia instead changed permanently by 1 percentage point, we estimate urban rents will expand by 1.6 percentage points faster than suburban rents permanently.

A key quantitative question is where we are in between these fully transitory and fully permanent cases. We use unique survey data from Pulsenomics, which asked a panel of real estate professionals in February 2021 whether they thought that the change in working from home was permanent or transitory. Thirty-six percent of respondents thought the change was permanent, while the rest thought it was transitory. We use this probability to interpolate between the transitory and permanent cases of the present-value model to arrive at our preferred estimate of the expected future rent growth in urban relative to suburban areas. According to this mixture model, urban rent growth is expected to exceed suburban rent growth by 3.5 percentage points in 2021 in the average MSA. The rent growth differential then gradually decreases to about 0.80 percentage points. In other words, the model points to a long-lasting urban revival as WFH recedes.

**Related Literature.** Our research builds on a large body of literature examining the role of urban land gradients in the context of agglomeration effects. Albouy, Ehrlich, and Shin (2018) es-
Albouy (2016) interprets the urban land premium in the context of local productivity, rents, and amenity values, building on the influential spatial equilibrium approach of Rosen (1979) and Roback (1982). Moretti (2013) argues that skilled workers have increasingly sorted into expensive urban areas, lowering the real skilled wage premium. A key finding from this literature is that productive spillovers and amenity values of cities account for the steep relationship between real estate prices and distance, the importance of which has been growing over time—particularly for skilled workers. We find strong and striking reversals of this trend during the COVID-19 period, especially for cities with the highest proportions of skilled workers, who can most often work remotely.

A large and growing literature investigates the effect of COVID-19. One strand of this research has examined the spatial implications of the pandemic on within-city changes in consumption resulting from migration, changing commutes, and changing risk attitudes (Althoff et al. (2020); De Fraja, Matheson, and Rockey (2020)). A number of contemporaneous contributions have begun to assess the impact of COVID-19 on real estate markets. Delventhal, Kwon, and Parkhomenko (2022) propose a spatial equilibrium model with many locations, in which households can choose where to locate in response to increased remote working opportunities. Davis, Ghent, and Gregory (2021) likewise studies the effect of working from home on real estate prices. Liu and Su (2021) examines changes in real estate valuation as a function of density—whereas this study focuses on the urban bid-rent curve and what the conjunction of prices and rents tell us about future rent expectations. Ling, Wang, and Zhou (2020), Garcia, Rosenthal, and Strange (2021) study the impact of the pandemic on asset-level commercial real estate categories. Our focus is on residential real estate and changes in rents and prices resulting from household migration. Brueckner, Kahn, and Lin (2021) also examines changes in residential valuations; with a main focus on the spatial equilibrium implications of working from home across cities. Our work is complimentary in highlighting the intra-city consequences, as well as in making inference on the persistence of the work-from-home shock from the relative changes in prices and rents.

Research in real estate finance has begun to use high-frequency location data from cell phone
ings to study patterns of consumption, commuting, and migration (Miyauchi, Nakajima, and Redding (2021); Couture et al. (2021); Gupta, Van Nieuwerburgh, and Kontokosta (2022)). Coven, Gupta, and Yao (2020) shows that the pandemic led to large-scale migration. This migration is facilitated by increased work-from-home policies and shutdowns of city amenities—both of which raised the premium for housing characteristics found in suburbs and outlying areas such as increased space.

We also connect to asset pricing research that decomposes stock price movements into transitory and long run shocks (Van Binsbergen, Brandt, and Koijen (2012); Van Binsbergen et al. (2013)). Gormsen and Koijen (2020) finds that stock markets priced in the risk of a severe and persistent economic contraction in March 2020 before revising that view later in 2020. Campbell et al. (2009) were the first to apply the present value model of Campbell and Shiller (1988) to real estate. They studied a variance decomposition of the aggregate residential house price-rent ratio in the U.S. Nieuwerburgh (2018) applied the model to REITs, publicly traded vehicles owning (mostly commercial) real estate.

The rest of the paper is organized as follows. Section 2.2 describes our data sources. Section 2.3 describes our results on the price and rent gradient estimation, as well as on migration. Section 2.4 studies cross-sectional variation in the price and rent gradients to assess the underlying mechanisms. Section 2.5 uses a present-value model to extract market expectations about the future expected rent changes from the relative changes in price and rent gradients. The last section concludes. Appendix B.1 provides additional results. Appendix B.2 contains additional details on data construction and representativeness, and Appendix B.3 contains additional information on price and rent decomposition.

2.2 Data

We focus on the largest 30 MSAs by population, presented in Table B.1 in Appendix B.1. Our core data focuses on measuring rent and price gradients, for which we use Zillow data at the ZIP
level.\textsuperscript{4} For prices, we focus on the Zillow House Value Index (ZHVI), which adjusts for house characteristics using machine learning techniques for a sample of all residential properties; and for rents we use the Zillow Observed Rental Index (ZORI), which is a constant-quality rent index capturing asking rents. Housing units include both single-family and multi-family units for both the price and the rent data series. Appendix B.2 describes this data, and in particular the construction and coverage of the ZORI data, in more detail. This section also directly compares Zillow rental data with rental data from Department of Housing and Urban Development (HUD), the American Community Survey (ACS), the Apartment List Rent Data, and data used in the Consumer Price Index (CPI) to establish broad similarity of rental data across different data providers. To ensure ease of comparison in price and rent gradient estimates, our main results are for a common sample of ZIP-month observations for which both the ZHVI and ZORI data are available. We explore robustness to a sample which uses all ZIP-month observations, and use the same set of controls when examining this broader sample.

To measure changes in housing inventory, we also use monthly data from the listing agent Realtor for all the ZIP codes in the U.S. Specifically, we use median listing price, median listing price per square foot, active listing counts, and median days a property is on the market.

We connect housing changes with migration using two datasets to capture high-frequency population moves. We measure changes in physical presence using data from VenPath, a holistic global provider of compliant smartphone data. We obtain information from approximately 120 million smart phone devices containing information on geographical location for users. We combine information from both background pings (location data provided while applications are running) as well as foreground pings (while users are actively using an application) to determine user residence and migration over the period February 1, 2020 to July 13, 2020. We also draw on migration information from Infutor, which covers address changes from a sample of close to 150 million properties.

We link changes in house prices and rents with covariates at both MSA and ZIP levels. A

\textsuperscript{4}The data are publicly available from https://www.zillow.com/research/data/.
crucial measure for the paper is the measurement of remote work. We use the Dingel and Neiman (2020) measure of the fraction of local jobs which can potentially be performed remotely. We use this variable both at the MSA level and at the ZIP-code level. We also measure the stringency of local lockdowns during the pandemic using the MSA-level measure of Hale et al. (2020). Also at the MSA-level, we measure constraints on local housing development by combining three measures commonly used in the literature. The Wharton regulatory index (Gyourko, Hartley, and Krimmel (2021)) captures man-made constraints on urban construction. We also measure physical constraints on housing using using the Lutz and Sand (2019) measure of land unavailability and the Saiz (2010) measure. We estimate the first principal component of these three measures, which we label the supply inelasticity index.

We also incorporate ZIP code level variables from the 2019 ACS. We measure the median household income, the median age of the head of household, the proportion of Black residents, and the proportion of residents who make over $150k. We also define, at the ZIP level, a measure of number of bars and restaurants from Safegraph to proxy for local amenities, defined as the count of full-service restaurants, limited-service restaurants, snack and non-alcoholic beverage bars, and drinking places (alcoholic beverages).

2.3 Results

We begin by showing descriptive evidence of price and rent changes across ZIP codes to highlight increased suburban rents and prices. We first show evidence for New York City and San Francisco—two of the real estate markets most affected by the pandemic. We then move to main estimates pooling across the largest 30 metropolitan areas, and discuss a number of other MSAs in Appendix B.1.

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5We calculate the ZIP-level WFH metric using the occupational make-up of the ZIP code and each occupation’s specific WFH rating.

6We use the 2016 values for all MSAs, except for Las Vegas where we use the Gyourko, Saiz, and Summers (2008) survey due to the unavailability of 2016 estimate.
2.3.1 Raw Price and Rent Growth

We first highlight the geography of changes in prices and rents for New York and San Francisco in Figure 2.2 over the period December 2019–December 2020. We observe strong rent decreases in the urban core (Manhattan, centered around Grand Central Terminal) and rent increases in the suburbs, with particularly high shifts in the Hamptons on the far east of the map. The pattern for price changes is similar, but less extreme. For San Francisco, we also see dramatic decreases in rents and prices in the downtown ZIP codes, and increases in more distant regions such as Oakland.

2.3.2 Bid-Rent Function

We next examine changes in prices and rents at the ZIP code level across a broad sample of the 30 largest MSAs in the U.S. Figure 2.3 highlights the relationship between rents (Panel A) and prices (Panel B) against distance from the city center, comparing pre- and post-pandemic patterns. We observe flatter relationships for both prices and rents, with larger changes in the slope of the bid-rent curve for rents than in the curve for prices.

A flattening bid-rent function implies that rent or price changes are higher in the suburbs than in the center. An alternative way of seeing this pattern is to plot the changes in rents (Panel C) and changes in prices (Panel D), for each ZIP code, against distance to the center of the city. We observe strongly decreasing rents in ZIP codes in the urban core, and strongly rising rents in suburban ZIP codes. For house prices, urban ZIP codes feature smaller price increases than suburban ZIP codes.

When plotted against the pre-pandemic levels, the changes in rents and prices indicated strong reversals of value in the most expensive ZIP Codes (Panels E & F of Figure 2.3). These findings highlight that price and rent reversals have been largest in areas which previously enjoyed large urban premiums.

Appendix Figures B.1-B.3 highlight the relationship between rents, prices, rent changes, price changes, and distance for New York and San Francisco.
Figure 2.2: Price and Rent Growth, NYC and SF

Notes: This map shows year-over-year changes in prices (top four panels) and rents (bottom two panels) for the New York and San Francisco MSAs at the ZIP code level over the period December 2019–December 2020. The bottom two rows zoom in on the city center. Darker green colors indicate larger increases, while darker red colors indicate larger decreases.
Figure 2.3: Pandemic Induced Changes in Prices and Rents

Bid-Rent Curve

(A) Rent

(B) Price

Changes Against Distance

(C) Rent

(D) Price

Changes Against Pre-Pandemic Levels

(E) Rent

(F) Price

Notes: The top two figures show the bid-rent function for the top 30 MSAs: the relationship between distance from the city center (the log of 1 + the distance in kilometers from City Hall) and the log of rents (Panel A) and prices (Panel B). Lighter points indicate ZIP codes, while darker points indicate averages by 5% distance bins (binscatter). Subsequent figures show changes in rents (Panels C & E) and prices (Panels D & F) against distance and the pre-pandemic levels of rents and prices. These figures are generated using those ZIP codes that have both rent and price data available.
2.3.3 Estimating the Bid-Rent Function

Next, we formally estimate the slope of the bid-rent function using the following empirical specification:

\[
\ln p_{ijt} = \delta_t \left( \text{Month}_t \times \left[ \ln (1 + D(z_{ij}^c, z_{ij}^m)) \right] \right) + \beta X_{ij} + \alpha_t \text{Month}_t + \alpha_j \text{MSA}_j + e_{ijt}. \tag{2.1}
\]

The unit of observation is a ZIP code-month. Here \( p_{ijt} \) refers to the price or rent in ZIP code \( i \) of MSA \( j \) at time \( t \), and \( D(z_{ij}^c, z_{ij}^m) \) is the distance in kilometers between the centroid of ZIP code \( i \) and the center of the MSA \( j \), where \( i \in j \).\(^7\) We control for time fixed effects (\( \alpha_t \)), MSA fixed effects (\( \alpha_j \)), and ZIP-code level control variables (\( X_{ij} \)). The ZIP-code controls are: log of annual median household income, median age of the head of household, proportion of Black households, and proportion of households who earn over $150k. The controls are all measured pre-pandemic, based on the latest available data from the ACS in 2019, and do not vary over time during our estimation window. Our main estimation sample restricts to ZIP code-month observations for which we have both price and rent data to ensure comparability of price and rent gradients.\(^8\)

The key coefficient of interest is \( \delta_t \) which measures the elasticity of prices or rents to distance between the ZIP code and the center of the MSA in any given month \( t \). We refer to it as the price or rent gradient. Historically, \( \delta_t \) is negative, as prices and rents decrease as we move away from the city center. An important statistic of interest is \( \Delta \delta \equiv \delta_{Dec2020} - \delta_{Dec2019} \), shown in Figure 2.1, which is the change in gradient over the period from December 2019–December 2020. We observe rising gradients over this time period, which means that properties away from the city center have become more valuable over the course of 2020, flattening the bid-rent curve. As emphasized, the increase in the rent gradient of 0.032 is more pronounced than the increase in the price gradient of

\(^7\) We define the center of the MSA as City Hall, as in Albouy, Ehrlich, and Shin (2018), except for New York City, in which we define Grand Central Terminal as the center.

\(^8\) We use all ZIP codes within the MSA boundary with price and rent data for our analysis. We find similar results when enforcing distance limits within MSAs which restrict to 1) the smallest maximum distance from the center based on top 6 MSAs; 2) the smallest maximum distance from the center based on top 30 MSAs; 3) the 25th percentile of the maximum distance from the center based on top 30 MSAs; and 4) the 75th percentile of the maximum distance from the center based on top 30 MSAs.
We find flattening bid-rent curves across samples. Figure 2.4 explores estimates of the price gradient based on different samples of ZIP codes, weighting schemes, and property sub-types. Panels B, C, and D use all ZIP codes for which there is price data but not necessarily rent data. In Panel B, there is no weighting, in Panel C we exclude ZIP codes with populations below 5,000, and in Panel C we estimate the panel regression weighting ZIPs by their population. We find increases in the average price gradient in each panel. The changes in gradient across samples are smaller than the baseline estimate since the baseline sample is tilted towards ZIP codes with higher population. Indeed, excluding ZIP codes with small populations or population-weighting ZIP codes results in larger gradient changes.\footnote{Figure B.4 finds similar results reproducing Figure 2.3 by including all ZIP codes with price data.} Across property types in Panels E-H, we find particularly large increases in gradients among condos/co-ops and small apartments and smaller increases for single-family housing. Overall, this evidence suggests that changes in prices were stronger in areas that had higher population (density) and more multi-family housing. Households in single-family homes would naturally be better equipped to work from home and find shelter from the pandemic.

In Section 2.4 we analyze the cross-sectional variation in rent and price gradient changes across MSAs. For that exercise, we estimate the following regression MSA-by-MSA for the top 30 MSAs:

\[
\ln p_{ijt} = \delta_{jt} \left( \text{Month}_{jt} \times \left[ \ln(1 + D(z_{ij}, z_{ij}^m)) \right] \right) + \beta_j X_{ij} + \alpha_{jt} \text{Month}_{jt} + e_{ijt}. \tag{2.2}
\]

The main object of interest is the gradient change for each MSA \( j \): \( \Delta \delta_j \equiv \delta_{j,Dec2020} - \delta_{j,Dec2019} \) for \( j = 1, 2, \ldots, 30 \). It captures the changing valuation of urban versus suburban prices and rents across urban areas. Figure 2.5 shows the change in price and rent gradient across U.S. metros.

### 2.3.4 Listing Prices

As an alternative to Zillow prices, and to explore homeowners’ listing behavior, we also study list prices from Realtor. Panels A and B of Figure 2.6 show that listing price prices (median and median price per sq. ft.) are increasing with distance from the city center, consistent with...
Figure 2.4: Robustness in Bid-Rent Curve Estimation Across Price Series

Notes: This plot shows bid-rent function slope coefficient estimates $\delta_t$ from a panel regression at the ZIP code level for the top 30 MSAs over the period January 2018–December 2020 following equation (2.1). The panels also report $\Delta \delta$: the change in gradient from Dec 2019 – Dec 2020. Panel A is the benchmark specification, which repeats the house price gradient plotted in Panel B of Figure 2.1. Panel B estimates the same price gradient from a sample of all ZIP Codes with house price data. Panel C includes all ZIPs, but restricts to those for which the Census ACS population from 2019 was at least 5,000. Panel D uses all ZIPs, but population-weights the gradient estimation. Panels E-H focus on different Zillow housing submarkets indices: one bedroom, two bedroom, condo/co-op units, and single family homes for the benchmark sample.
Figure 2.5: MSA level Changes in Price and Rent Gradients

Notes: This map plots the change in price and rent gradients across the U.S. over the period December 2019–December 2020. For each MSA, we estimate the price and rent gradient as in equation (2.2), and plot the resulting change ($\Delta \delta_f$) at the MSA-level. Higher values correspond to a flatter bid-rent curve. The size of the circle corresponds to the magnitude of the change.
the evidence from transactions prices. This result confirms a greater increases in suburban prices relative to urban prices using an alternate measure of prices.\textsuperscript{10}

Figure 2.6: Changes in Listing Prices and Market Inventory

Notes: The relationship between changes in listing prices, measured as either the median listing price (Panel A) or the median listing price per sq. ft. (Panel B) with respect to distance. Changes in two measures of market inventory, active listings (Panel C) and median days on market (Panel D) against distance from the center of the city the top 50 MSAs in the US. Each observation is a ZIP Code and represents the change in the market inventory or listing price measure from December 2019 to December 2020. These figures are generated using those ZIP codes that have both rent and price data available.

\textsuperscript{10} Appendix Figure B.5 shows a very similar relationship for a larger sample of all ZIPs for which we have house price data. Figure B.6 shows the changes in the log median listing price for New York and San Francisco metropolitan areas (Panel A), and changes in the log of median listing price per square foot (Panel B). It confirms the full-sample patterns.
2.3.5 Quantity Adjustments

Next we assess two measures of housing quantities, which are often interpreted as measures of liquidity. Active listings measures the number of housing units that are currently for sale. Panel C of Figure 2.6 shows a large increase in the housing inventory in the urban core between December 2019 and December 2020 and a large decline in inventory in the suburbs. Buyers depleted large fractions of the available housing inventory in the suburbs during the pandemic, even after taking into account that a strong sellers’ market may have prompted additional suburban homeowners to put their house up for sale over the course of 2020.

The second measure we study is median days-on-the-market (DOM), a common metric used in the housing search literature (Han and Strange (2015)) to quantify how long it takes to sell a house. Panel D of Figure 2.6 shows that DOM rose in the urban core and fell in the suburbs. Housing liquidity improved dramatically in the suburbs and deteriorated meaningfully in the center.\(^\text{11}\)

There is a strong negative cross-sectional relationship between house price changes and changes in active listings across all ZIP codes of the top-30 metropolitan areas in the U.S. (Figure 2.7). ZIP codes in the suburbs are in the top left corner of this graph while ZIP codes in the urban core are in the bottom right corner.\(^\text{12}\)

2.3.6 Migration

These large changes in real estate markets correspond to substantial revaluations of urban premia in the context of the pandemic shock of COVID-19. In this section, we connect these valuation changes to the migration pattern of individuals over this time period, and the role of remote work in facilitating these moves.

To measure home residence, we use mobile phone geolocation data provided by VenPath. We measure individual night-time residence based on frequency of pings at night hours.\(^\text{13}\) We observe

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\(^\text{11}\)Figure B.6, Panel C, shows similar results for New York and San Francisco.
\(^\text{12}\)The same relationship holds for a larger sample of all ZIPs for which we have house price data; see Figure B.7.
\(^\text{13}\)We require three or more pings nighttime pings in a given census tract to designate a user as a possible resident, and require at least five associations of individuals with nighttime pings in the same location in the same month to assign a residence. Our definition of nighttime is from 5pm–8am, but results are robust to the alternative nighttime
(A) Price change against active listing changes  

Notes: Changes in prices against changes in two measures of inventories. Panel A plots the relationship between the percentage change in house prices from Dec 2019–Dec 2020 against the percentage change in active listings over this period. Panel B plots the same change in house prices against the percentage change in days on market over the same period. These figures are generated using those ZIP codes that have both rent and price data available.

We connect these population changes to remote work in Panel B of Figure 2.8, using a ZIP level measure of the fraction of jobs which could potentially be done remotely by Dingel and Neiman (2020). We find a strong association between population flight and the share of the population in the ZIP that is able to work remotely, suggesting that workers with flexibility in their work location were particularly likely to leave their home ZIP codes during the pandemic.

We also connect migration patterns to changes in rents (Panel C) and prices (Panel D). We find a particularly strong association of migration and changes in rent, but still meaningful correlation with price changes, suggesting that the housing markets may be affected for the long-run.\textsuperscript{14}

Figure B.10 reports the relationship between population changes and distance, and between rent and price changes on the one hand and population changes on the other hand for New York definitions of 10pm–8am and 4am–8am. Appendix Figure B.8 finds similar results for the population change across location gradients for the different definitions of nighttime residence.

\textsuperscript{14}The results are robust to examining the full sample of ZIP codes with house price data; see Figure B.9.
and San Francisco, finding a considerable exodus to the suburbs for these two superstar cities.

Figure 2.8: Associations of Intracity Migration

Notes: This figure shows the change in population from February to March as measured in VenPath against log(1 + distance) to the city center (Panel A) and Dingel and Neiman (2020) WFH metric for the top 30 MSAs (Panel B). We then connect changes in population plotted against changes in rents at the ZIP level (Panel C) and changes in prices (Panel D) for the top 30 MSAs. These figures are generated using those ZIP codes that have both rent and price data available.

We find similar migration patterns when we contrast the home Census tract of individuals (based on nighttime activity) in February with their changed location in March of 2020. This measure only captures migration rates of individuals which we are able to consistently track in both months. This within-user analysis is more demanding, but guards against the possibility that the population counts in the previous graph reflect data coverage changes rather than migration.
Figure 2.9: Out-Migration Rates Using VenPath Data

Notes: This figure plots the out-migration rate at the ZIP level from VenPath across three MSAs: New York, San Francisco, Boston, as well as a broad sample of all MSAs considered in Table 2.3. To measure out-migration, we examine an individual’s home Census tracts in February based on their preponderant nighttime ping activity. We then examine their home tract at the end of March, and estimate out-migrants as those individuals who have changed their home tract. Individuals who drop out of the data are not considered.
Figure 2.9 reports the within-user out-migration rates. We observe high out-migration rates of individuals close to the city center. Appendix Figure B.11 shows that these relationships persist for net migration, so that outflows from urban areas are not fully offset by greater inflows from elsewhere.

We consider a second data source, Infutor, to measure migration patterns during the pandemic. The Infutor data measure changes of address, covers about 150 million residences and has been used in prior literature (Diamond, McQuade, and Qian (2019)) to study migration. For our purposes, we consider changes of address between March 1, 2020 and the end of October 2020. This serves not only as a robustness check on our cell phone ping results, but may also speak to the lasting nature of the relocation. Changes of address may capture mostly persistent relocation (changing homes is costly to reverse), while the cell phone ping data may capture both transitory and persistent moves.

Figure 2.10 highlights an urban gradient using out-migration rates drawn from the Infutor data. We show similar migration gradients with respect to distance from the city center for the New York, San Francisco, and Boston metropolitan areas, as well as for a five-city sample which also adds Los Angeles and Chicago. Out-migration rates are high near the urban core and low in the suburbs. These results complement our mobile phone location data in suggesting that changes in physical location also result in changes in residence as measured by changes in address. This section has shown large migration away from the center of cities that began at the onset of the pandemic. This relocation was boosted by several factors. Initially, there was considerable concern that densely populated metropolitan areas presented additional risk for disease transmission. Additionally, the ensuing lockdowns lowered the value of local amenities such as restaurants and bars. Through both government-enforced closures as well as voluntary cutbacks in behavior, the value of these urban consumption goods was drastically lowered, further diminishing the value of urban life. Work-from-home (WFH) policies also enabled many workers to work remotely rather than commute to work. These WFH policies were born out of necessity because offices were not allowed to reopen.

As the pandemic wore on, and cities gradually reopened, the continued ability to work from
home became a major source of uncertainty for individuals. Some employers have since signaled the possibility of long-lasting remote work policies, either towards a fully-remote workforce or towards hybrid forms of remote work several days a week for a large share of employees. These partial remote policies may explain the permanent relocation of individuals to the outskirts of metropolitan areas indicated by the Infutor analysis, as workers anticipate less frequent commutes. The remainder of the paper studies the persistence in these trends, first using a cross-sectional analysis in Section 2.4 and then a time-series analysis in Section 2.5.
Figure 2.10: Out-Migration Rates Using Infutor Data

Notes: This figure plots the out-migration rate from Infutor across three MSAs: New York, San Francisco, Boston, as well as sample of five MSAs which also includes Los Angeles and Chicago. Residents are included if Infutor reports an active date for that individual after January 1, 2019—this restriction is used to remove inactive or deceased individuals. Migration is measured by estimating whether any individuals have an address change to another location over the period from March 1, 2020–October 31 2020. Dots correspond to ZIP codes with at least 5,000 in measured population.
2.4 Mechanisms

Having established the change in price and rent gradient at the metropolitan level, in this section we examine the main driving factors behind the changes in the bid-rent function in the cross-section.

2.4.1 MSA-Level Analysis

We first explore the potential drivers of increased suburban valuation for rents and prices by exploiting variation across MSAs. We focus on three key variables: the fraction of the population with occupations that can be done remotely (Dingel and Neiman (2020)), COVID-19 lockdown restrictions from Hale et al. (2020), and a measure of housing inelasticity (the first principal component of the Saiz (2010) supply elasticity measure, the Gyourko, Hartley, and Krimmel (2021) land use regulatory index, and the Lutz and Sand (2019) measure of land availability).

We regress the change in the rent gradient for each of the top 30 MSAs against several MSA-level characteristics in Panel A of Table 2.1. Panel B of Table 2.1 presents the results for the change in the price gradient as the dependent variable. Column (1) shows that variation in remote work (Dingel and Neiman (2020)) across MSAs alone explains 27.8% of variation in rent gradient changes and 21.0% of variation in price gradient changes, and is a strong economic predictor of changes in these gradients. A 10% point increase in the fraction of jobs in an MSA which can be done remotely changes the rent gradient by 3.02% points and the price gradient by 2.15% points. These are substantial increases which reflect large revaluations of suburban vs. urban real estate in areas with more remote work.

The larger positive coefficient on WFH for rents compared to prices indicates a greater reversal in rent gradients versus price gradients across MSAs. As rents reflect short-term expectations, and prices—which are forward-looking—capture expectations of real estate markets over longer

\[15\] We associate each MSA with the preponderant state in the area to assign lockdown policies; for instance the NYC MSA with New York State.

\[16\] Table B.1 reports the rent and price gradient changes for each MSA which are the dependent variables of these cross-MSA regressions.
horizons, this evidence supports the urban revival results we will find in Section 2.5.6. An expected future reduction in work from home practices relative to the high 2020 WFH levels would result in higher urban rents. At the same time, the substantial impact on price gradients suggests that some of the effect is expected to be long-lived.

While this specification shows the importance of remote work in accounting for the cross-section of urban real estate repricing, WFH may affect housing markets through two important channels. One channel is that workers who could theoretically work remotely saw this possibility realized over the course of the pandemic. Survey data suggest that many employers and employees expect remote work to continue in the future, at least on a hybrid basis.\footnote{Survey evidence in Barrero, Bloom, and Davis (2021) indicates a persistence in remote working policies.} The ability to work from home allowed households to re-optimize their housing choices, move away from the urban centers without increasing their commuting times.

At the same time, the class of workers who can work remotely, which consists of mostly higher-skilled workers, have historically also preferred cities for reasons of urban amenities (Couture et al. (2019); Guerrieri, Hartley, and Hurst (2013)). If these workers have experienced a shift in their preference for urban amenities, the resulting reallocation could also lower urban gradients—even if these workers still anticipate regular commuting in the future.

We are able to measure one possible component of amenity revaluation in column (2), which measures policy lockdown measures. These correspond to government-imposed restrictions in private activity, which directly affected the ability of residents to take advantage of local amenities. This variable is normalized to be the same range (0–1) as the WFH measure to enable comparability. We find that MSAs which feature more strict COVID restrictions see more revaluation towards suburban properties. The effects are substantial for rents, with a coefficient of 0.19 and a $R^2$ of 21.3%. They are smaller for prices with a coefficient of 0.128 and a $R^2$ of 14%. Yet, for both rent and price gradients, the impact of lockdowns is smaller than for the WFH variable.

We also investigate the role of housing supply inelasticity in column (3), again normalized to be the same range (0–1) as the WFH measure. Cities where urban premia reflect supply constraints
also see urban revaluation in house prices (but not in rents), suggesting that affordability constraints in superstar cities may drive interest in suburban lifestyles. The magnitude of the effect is again smaller than for WFH.

We combine all three variables under two sets of assumptions in columns (4) and (5). In column (4) we include all three variables in conjunction. These three variables combined explain 37.2% of the cross-MSA variation in rent gradient changes and 30.6% of the variation in price gradient changes across MSAs. The WFH measure remains large and economically significant for both rent and price gradient changes, showing the importance of remote work in explaining the reversal of the price and rent gradients. Individuals highly value the importance of remote work leading to increases in suburban valuation. The stringency measure and the supply inelasticity become much smaller and insignificant determinants for both rent and price gradients.

The work from home measure might be correlated with the stringency and supply inelasticity index. In column (5), we orthogonalize the stringency and supply inelasticity index to the WFH measure. The effect of remote work is naturally larger in Column (5) as compared to Column (4) as the coefficient soaks up the common variation which was earlier attributed to other measures. However, the coefficients on the orthogonalized stringency and supply inelasticity measures do not change much in magnitude, suggesting that there is not much correlation between these variables in the first place.

In Appendix Figure B.12, we decompose the effects for each MSA based on our estimates from column (5) for rents and prices. While MSAs broadly see changes in urban valuation due to remote work policies, there is considerable variation in the cross-section due to the prevalence of remote work. Many superstar metro areas like New York, San Francisco, Washington, and Seattle feature high amounts of remote work, and correspondingly see large changes in the valuation of urban properties. By contrast, other metro areas like Orlando, Detroit, and Pittsburgh have far less remote work. Some metros like Charlotte, Austin, and San Antonio see a partial offset of the WFH effect due to more elastic housing supply. In these areas, the relative ease of building means that greater real estate demand results in higher quantities of real estate supplied, rather than higher
prices.

Table B.2 shows robustness of the results on the cross-MSA determinants of price gradient changes for gradients estimated from different samples of ZIP codes and different types of owner-occupied housing.

Our preliminary conclusion from the MSA-level analysis is that the WFH effect reflects the importance of commuting costs relative to urban amenities. We refine this analysis next with ZIP-level analysis.

2.4.2 ZIP-Level Analysis

Next, we revisit the commuting-versus-amenities question at the finer level of granularity of the ZIP code. This analysis uses a ZIP-level WFH measure as well as a measure of ZIP-level amenities, namely the number of bars and restaurants. We also include MSA fixed effects which captures amenities common to the metropolitan area.

In Table 2.2, Panel A, we regress rent changes from Dec 2019–Dec 2020 against a variety of ZIP-level covariates. Panel B repeats the estimation for price changes. We find that the fraction of remote workers at the ZIP-code level remains strongly predictive of real estate changes even after controlling for MSA-fixed effects and ZIP-level amenities, alongside other socio-economic covariates.\(^{18}\)

For rents, a 10% point increase in the fraction of remote work in a ZIP code is associated with a 1.3–2.5% point decrease in rent growth, depending on the specification. The number of restaurants and bars, a measure of the pre-pandemic amenity value of a ZIP code, also predicts declines in rents.

The WFH measure also is an important driver of ZIP-level variation in house price growth within the MSA (Panel B), with a 10% point increase in remote workers decreasing local house price growth by between 0.5–1.9% points. The estimates for the impact of remote work remain

\(^{18}\)Results do not change when we use the orthogonalized work from home measure to log of income. In the case of New York City, where the count of COVID-19 cases and deaths are available at the ZIP-code level, we find that the effect is not driven by these COVID variables; the work from home measure remains significant.
economically and statistically significant after controlling for ZIP-level covariates.

The nature of our controls enables us to make stronger statements about the nature of the WFH shock at the ZIP-level. Because MSA fixed effects and the ZIP-level measure of restaurants and bars should account for a substantial component of the association of local amenities and real estate valuation, the residual association of WFH and real estate outcomes likely reflects the importance of the remote worker reallocation channel. This reflects the ability of workers with remote jobs to change where they live. In principle, the disconnection of living and working could have either pro-urban or pro-suburban tilts. Some workers may use the flexibility of work to actually relocate towards cities, while other workers will use flexibility to head towards cheaper suburban areas. On net, we find that the nature of urban revaluation is for remote workers to leave expensive urban areas for less expensive suburban locations within their MSAs now that they need to commute to the office less frequently.
Table 2.1: Determinants of Cross-MSA Variation in Rent and Price Gradient Changes

(A) MSA-Level Rent Changes

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<tr>
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<th>(2)</th>
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<th>(4)</th>
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</tr>
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<tbody>
<tr>
<td>Work from Home</td>
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<td>0.239**</td>
<td>0.302***</td>
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<tr>
<td></td>
<td>(0.0919)</td>
<td>(0.0950)</td>
<td>(0.0891)</td>
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<td></td>
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</tr>
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<td>Supply Inelasticity Index</td>
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<td></td>
<td>(0.0156)</td>
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<td>(0.0148)</td>
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<tr>
<td></td>
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<td>(0.0690)</td>
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<tr>
<td>Orthogonalized Supply Inelasticity</td>
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(B) MSA-Level Price Changes

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<tr>
<td>Work from Home</td>
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<td>0.174**</td>
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<tr>
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<td>(0.0789)</td>
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<td>Supply Inelasticity Index</td>
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<td>0.140</td>
<td>0.125</td>
<td>0.306</td>
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</table>

Notes: In both panels, we first estimate a gradient specification separately for each MSA following our equation (2.2). We then calculate $\delta_{t,\Delta} = \delta_{t,\text{Dec}2020} - \delta_{t,\text{Dec}2019}$ from this specification, corresponding to the change in gradient, for each MSA, over the period December 2019–December 2020. The change in rent gradient is key dependent variable in Panel A and the change in the price gradient is the dependent variable in Panel B. We regress this gradient change against three independent variables at the MSA-level: the Dingel and Neiman (2020) WFH measure, a lockdown stringency measure from Hale et al. (2020), and a housing supply inelasticity index (the first principal component of the Saiz (2010) supply elasticity measure, the Gyourko, Hartley, and Krimmel (2021) land use regulatory index, and the Lutz and Sand (2019) measure of land availability). Column (5) orthogonalizes stringency to the WFH variable and land inelasticity to both WFH and stringency measures. Standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.
Table 2.2: Intra-city Rent and Price Changes

(A) ZIP-Level Rent Changes

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<tr>
<td>Log(Distance)</td>
<td>0.0298**</td>
<td>0.0241***</td>
<td>0.0253***</td>
<td>0.0149***</td>
<td>0.0173***</td>
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<tr>
<td></td>
<td>(6.15)</td>
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<td>(6.37)</td>
<td>(4.14)</td>
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<tr>
<td>Work from Home</td>
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<td>-0.251***</td>
<td>-0.195***</td>
<td>-0.125***</td>
<td>-0.147***</td>
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<tr>
<td></td>
<td>(-8.73)</td>
<td>(-8.15)</td>
<td>(-12.16)</td>
<td>(-7.38)</td>
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<td>Median Household Income ('000)</td>
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</tr>
<tr>
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<td>(5.66)</td>
<td>(8.03)</td>
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<tr>
<td>Median Age</td>
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<td>0.00103***</td>
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<tr>
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<td>(4.22)</td>
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<tr>
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<td>(1.80)</td>
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<tr>
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<td>(0.36)</td>
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MSA fixed effects ✓ ✓ ✓ ✓ ✓ ✓
Observations 1697 1697 1697 1697 1697 1697
R squared 0.580 0.536 0.484 0.676 0.557 0.709

(B) ZIP-Level Price Changes

<table>
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<td>Log(Distance)</td>
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<tr>
<td>Work from Home</td>
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<td>-0.173***</td>
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<td>-0.108***</td>
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<td>0.000115**</td>
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<tr>
<td>Percent of Black Households</td>
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<td>Share of High Income Households</td>
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MSA fixed effects ✓ ✓ ✓ ✓ ✓ ✓
Observations 1697 1697 1697 1697 1697 1697
R squared 0.500 0.536 0.484 0.676 0.557 0.709

Notes: Panel A of this table shows a regression of changes in ZIP-level log rents from Dec 2019 to Dec 2020 against a variety of ZIP level covariates. Panel B shows a regression in which the change in log rents is the key dependent variable. Independent variables include: the Dingel and Neiman (2020) WFH measure constructed at a ZIP-level, a variety of controls from the 2019 ACS (median household income in thousands, median age of household head, percentage of Black households, and share of high income households), and the log of the number of restaurants and bars from Safegraph. The presence of MSA-fixed effects is indicated in the table bottom. The sample is restricted to ZIP codes for which we can measure both rent and price changes. Standard errors in parenthesis are clustered at the MSA level. * p < 0.10, ** p < 0.05, *** p < 0.01.
The comparison of WFH effects across rents and prices also points to the persistence of urban revaluation. Changes in rents reflect short-run changes in real estate markets; rents have to adjust (possibly drastically) to ensure that current supply and demand line up for rental properties. Changes in prices, however, also include a long-run expectations component as people purchase property in anticipation of changes in future rents. We find that WFH is more strongly associated with rent changes than price changes. The effect of WFH in our preferred specification in column (6) is \(-0.147\) for rents in Panel A and \(-0.108\) for prices in Panel B. This suggests that some component of WFH associated urban flight is temporary, reflecting particularly flexible remote working policies during this period which may not last. However, the effect of WFH on prices is also substantial at the ZIP level, pointing to the role of persistently changed (expectations) about future remote work policies and commuting patterns.

Table B.3 shows robustness of the results on the cross-ZIP determinants of price changes for different samples of ZIP codes and different types of owner-occupied housing.

2.5 Beliefs About Future Rent Growth

In this section, we investigate what housing markets tell us about future rent growth expectations following the COVID-19 shock. To do so, we combine the observed changes in the price and rent gradients with a present-value model to build expectations about the relative rent growth rate in suburbs versus the urban core over the next several years.

2.5.1 Observed Price-Rent Ratios

In the subsequent analysis we use price-rent ratios. Because the Zillow data are quality-adjusted, it is reasonable to interpret the price-rent ratio in a ZIP code as pertaining to the same typical property that is either for rent or for sale. For our purposes, it is enough that the change over time in the price-rent ratio is comparable across ZIP codes within an MSA.

We first calculate the price-rent ratio for each ZIP-month over the period of January 2014 (when the rent data starts) until December 2019. We then average over these 72 months. This average
acts as a proxy for the long-run equilibrium price-rent ratio before the pandemic. Price-rent ratios are high in the city center and decrease with distance to the center. The “Pre-Pandemic” line in Figure 2.11 illustrates this pattern for the New York MSA.

Figure 2.11: Price-Rent Ratio against Distance for New York

Notes: The figure shows the relationship between the price-to-rent ratio in New York City before the pandemic (Jan 2014 to Dec 2019, in green) and during the pandemic (2020 Q4, in red) across distance to the center of the city, measured as log of 1 + distance to Grand Central in kilometers.

We also compute the price-rent ratio in the fourth quarter of 2020, averaging the price-rent ratios of October, November, and December 2020.\textsuperscript{19} The “Post-Pandemic” line in Figure 2.11 shows the price-rent ratio at the end of 2020 in New York. In the suburbs, rents and prices rose by about the same amount over the course of 2020, leaving the price-rent ratio unchanged. In the urban core, rents fell much more than prices, resulting in a large increase in the price-rent ratio. Thus, the price-rent ratio curve became steeper during the pandemic. Put differently, it became relatively cheaper to rent than to own in the core.

Another way to see this is to plot the average 12-month rental growth rate over the January 2014 to December 2019 period as a function of distance from the city center of New York. Panel A of Figure 2.12 shows that rental growth was similar in the core and in the suburbs of New York City pre-pandemic. This pattern changes dramatically during the pandemic, with steeply falling rents in the core and steeply rising rents in the suburbs. Panel B shows a strong reversal in house

\textsuperscript{19}As long as the price-rent ratio in one of the months is available, the ZIP code is included in the analysis.
price growth as a function of distance before and after the pandemic. We also show, in Appendix Figure B.13, that these patterns reflect novel post-pandemic migration patterns, and are not simply a continuation of long-term migration trends.

Figure 2.12: Changes in Rent and Price Growth Rates

(A) Rent Growth

(B) Price Growth

Notes: This figure shows the changes in rental growth rates (Panel A) and price growth rates (Panel B) over the pre-pandemic period (Jan 2014–Dec 2019) compared with the period during pandemic (Oct 2020–Dec 2020) across distance from the center of New York, measured as the log of (1 + distance to Grand Central Terminal in kilometers).

2.5.2 Present-Value Model

We consider a present-value model in the vein of Campbell and Shiller (1988) to interpret the observed changes in the price-dividend ratio. Appendix B.3 contains additional details.

Starting with a basic definition of housing returns, we let \( P_t \) be the price of a risky asset, in our case the house, \( D_{t+1} \) its (stochastic) cash-flow, in our case the rent, and \( R_{t+1} \) the cum-dividend return:

\[
R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t}.
\]

By iterating forward, log-linearizing the definition of cum-dividend returns, and imposing a transversality condition, we obtain the present-value relationship equating the price-dividend ratio to the difference between the cumulative discounted expected rent growth rates, \( g_t = E_t[\Delta d_{t+1}] \),
and the cumulative discounted expected housing returns $x_t = E_t[r_{t+1}]$:

$$pd_t = \frac{k}{1-\rho} + \sum_{s=1}^{\infty} \rho^{s-1} g_{t+s} - \sum_{s=1}^{\infty} \rho^{s-1} x_{t+s}.$$  \hspace{1cm} (2.3)

This relationship holds for every ZIP code $i$ in every MSA $j$. We assume that ZIP codes were at their long-run averages $(\bar{x}^{ij}, \bar{g}^{ij})$ prior to the pandemic, in December 2019. They imply $\bar{pd}^{ij}$ per equation (2.3).

To make further progress on the relationship between current prices and future projections, we need to take a stance on whether the pandemic has transitory or permanent effects. We first discuss the details of our estimation under either condition, and then combine both cases based on survey evidence on the persistence of the covid shock.

### 2.5.3 Case 1: Pandemic is Transitory

In a first set of calculations, we assume that following the COVID-19 shock, expected rent growth and expected returns (and hence the mean $pd$ ratio) will gradually return to their pre-pandemic averages $(\bar{x}^{ij}, \bar{g}^{ij}, \bar{pd}^{ij})$. Under this assumption, we can ask what the observed changes in the price-rent ratios between December 2019 and December 2020 imply about the market’s expectations about rent growth in urban relative to suburban ZIP codes over the next several years.

If $pd_t$ is measured as of December 2020, then equation (2.4) below measures the percentage change in the price-rent ratio post versus pre-pandemic. Let $i = u$ denote a ZIP code in the urban core and let $i = s$ denote a ZIP code in the suburbs. Then the difference-in-difference of the price-rent ratio between post- and pre-pandemic and between suburban and urban ZIP codes in the same MSA is given by:

$$\Delta pd^{uj} = \left[ A^{uj} \left( g_{t}^{uj} - \bar{g}^{uj} \right) - A^{sj} \left( g_{t}^{sj} - \bar{g}^{sj} \right) \right] - \left[ B^{uj} \left( x_{t}^{uj} - \bar{x}^{uj} \right) - B^{sj} \left( x_{t}^{sj} - \bar{x}^{sj} \right) \right].$$ \hspace{1cm} (2.4)

$$\Delta pd^{ij} \equiv \left( pd_{t}^{ij} - \bar{pd}^{ij} \right) - \left( pd_{t}^{sj} - \bar{pd}^{sj} \right)$$

where the second line defines $\Delta pd^{ij}$ for an MSA $j$. 

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We observe $\Delta p d^j$, but there are two unknowns on the right-hand side. Hence, there is a fundamental identification problem which is well understood in the asset pricing literature. One either needs additional data on return expectations or on expected cash flow growth, for example from survey data, or one needs to make an identifying assumption. We follow the second route.

**Assumption 1** Expected returns and expected rent growth follow an AR(1) with the same persistence across geographies: $\rho^{ij} = \rho_x$ and $\rho^{ij} = \rho_g$. We also assume that $\rho^{ij} = \rho^i$.20

Under Assumption 1, we can use the present-value relationship to back out the market’s expectation in terms of expected rent growth in urban minus suburban ZIP codes:

$$g_t^{u_j} - g_t^{s_j} = \bar{g}^{u_j} - \bar{g}^{s_j} + (1 - \rho^j \rho_g) \Delta p d^j + \frac{1 - \rho^j \rho_g}{1 - \rho^j \rho_x} \Delta x^j$$

(2.5)

where

$$\Delta x^j \equiv (x_t^{u_j} - \bar{x}^{u_j}) - (x_t^{s_j} - \bar{x}^{s_j}).$$

Equation (2.5) gives the expected rent growth differential over the next twelve months, measured as of December 2020, i.e., between December 2020 and December 2021. But since expected rent growth follows an AR(1), there will be further changes in 2022, 2023, etc. The expected discounted cumulative rent changes over all future years are given by:

$$\frac{g_t^{u_j} - g_t^{s_j}}{1 - \rho^j \rho_g} = \frac{\bar{g}^{u_j} - \bar{g}^{s_j}}{1 - \rho^j \rho_g} + \Delta p d^j + \frac{\Delta x^j}{1 - \rho^j \rho_x}.$$  

(2.6)

$\Delta x^j$ measures to what degree the pandemic changed the risk premium on urban versus suburban housing. Estimating time-varying risk premia is hard, even in liquid markets with long-time series of data. It is neigh impossible for illiquid assets like homes over short periods of time like the 12-month period we are interested in. As such, the best we can do is define our assumptions and understand their impact. We consider two alternative assumptions on $\Delta x^j$.

20This is an approximation. The mean log price-rent ratio, $\bar{p}d^j$, and hence $\rho^{ij}$ depends on $(i, j)$ because of heterogeneity in $(\bar{x}^i, \bar{g}^i)$. We construct the population-weighted mean of $\bar{p}d^j$ across all zip codes in the MSA, call it $\bar{p}d^j$, and then form $\rho^j$ from $\bar{p}d^j$ using equation (B.1).
**Assumption 2** Expected returns did not change differentially in urban and suburban areas in the same MSA in the pandemic: $\Delta x^j = 0$.

This assumption allows for expected returns to be different in urban and suburban ZIP codes and for expected returns to change in the pandemic. It only precludes that this change was different for suburban and urban areas. Expected returns can be written as the interest rate plus a risk premium. Since the dynamics of interest rates (and mortgage rates more generally) are common across space, this assumption is one on the dynamics of urban-suburban risk premia.

Expected returns in suburban areas are typically higher than in urban areas pre-pandemic. The alternative assumption we make is that the pandemic narrowed this gap. Specifically, the annual urban risk premium increases by one percentage point relative to the suburban risk premium:

**Assumption 3** $\Delta x^j = 0.01$, $\forall j$.

Under this assumption the urban-minus-suburban risk premium increase is transitory: it initially increases by 1% point and reverts back to zero at rate $\rho_x$. Naturally, the model can handle any other change besides 1% point or a change that varies by MSA.

### 2.5.4 Case 2: Pandemic is Permanent

The opposite extreme from assuming that everything will go back to the December 2019 state is to assume that the situation as of December 2020 is the new permanent state.

In that case, we can again use the present-value relationship to back out what the market expects the new long-term expected urban minus suburban rent growth to be, denoting the new post-pandemic steady state by hatted variables:

$$\hat{g}^{uj} - \hat{g}^{sj} = \left(\hat{p}_{d}^{uj} - \hat{p}_{d}^{sj}\right) - \left(\log \left(1 + e^{\hat{p}_{d}^{uj}}\right) - \log \left(1 + e^{\hat{p}_{d}^{sj}}\right)\right) + \hat{x}^{uj} - \hat{x}^{sj}. \quad (2.7)$$

The first two terms can be computed directly from the observed price-rent ratios in December 2020. The last term requires a further assumption.
We consider the same two assumptions on post-pandemic urban minus suburban expected returns (or equivalently risk premia) as in the transitory case. The first one is that urban minus suburban risk premia differences remain unchanged pre- versus post-pandemic.

**Assumption 4** $\tilde{\bar{\mu}}^u - \tilde{\bar{\mu}}^s = \bar{\mu}^u - \bar{\mu}^s, \forall j$. We refer to this as $\Delta \bar{\mu}^j = 0$.

The second assumption is that urban risk premia rise relative to suburban risk premia by a constant amount of 1% point.

**Assumption 5** $\tilde{\bar{\mu}}^u - \tilde{\bar{\mu}}^s = \bar{\mu}^u - \bar{\mu}^s + 0.01, \forall j$. We refer to this as $\Delta \bar{\mu}^j = 0.01$.

The difference in comparison to the transitory case is that, now, the relative risk premium change is permanent.

### 2.5.5 Case 3: Combining Transitory and Permanent Cases

Let $p$ be the probability that the changes in the urban-minus-suburban expected rent growth and expected return are transitory, and $1 - p$ be the probability that the changes are permanent. In the subsequent section we incorporate survey evidence on $p$.

Denote $\tilde{g}^u_t$ and $\tilde{g}^s_t$ as the urban and suburban expected rent growth combining the transitory and permanent cases:

$$\tilde{g}^u_t - \tilde{g}^s_t = p(g^u_t - g^s_t) + (1 - p)(\tilde{g}^u_t - \tilde{g}^s_t).$$

(2.8)

The first term comes from equation (2.5), while the second term uses equation (2.7).

Similarly, let $\tilde{p}^u_t$ and $\tilde{p}^s_t$ denote the combined log price-rent ratios for the urban and suburban areas, respectively. The difference $\tilde{p}^u_t - \tilde{p}^s_t$ is the weighted average of the transitory and permanent cases:

$$\tilde{p}^u_t - \tilde{p}^s_t = p(p^u_t - p^s_t) + (1 - p)(\tilde{p}^u_t - \tilde{p}^s_t).$$

(2.9)
The first term is calculated from the transitory model, while the second term consists of the observed price-rent ratios in December 2020, which are considered to be the new long-run levels in the permanent case.

### 2.5.6 Results: Implied Urban-Suburban Rent Growth Expectations

We report results for each of the 30 largest MSAs in which rent data is available for at least some of the suburban areas (Table 2.3). In these specifications, we are interested in both rent and price information for not just the urban core, but also suburban areas.

We define the urban ZIP codes to be all ZIP codes less than 10 kilometers from the MSA centroid (city hall), and the suburbs to be the ZIP codes more than 40 kilometers from the MSA centroid. For each ZIP code, we compute the price-rent ratio in each month from January 2014 (the start of ZORI data) until December 2019, and compute the time-series average. Similarly, we compute the time-series mean of the average annual rental growth rate for each ZIP code over the 2014–2019 period. We then compute population-weighted averages among the urban and suburban ZIP codes (columns (1–4)). For presentation purposes, the mean price-rent ratio is reported in levels (rather than logs) and average rent growth is multiplied by 100 (expressed in percentage points). We use equation (B.4) in the appendix to compute the expected annual returns in columns (5) and (6). These expected returns are also multiplied by 100. Expected returns are between 5% and 14% per year. Typically, though not always, expected returns are higher in the suburbs. The numbers in columns (1–6) reflect the pre-pandemic steady state.

Columns (7) and (8) report the price-rent ratio (in levels) for last quarter of 2020. Column (9) reports $\Delta pd$, the log change in the urban-minus-suburban price-rent ratio during the pandemic versus before the pandemic. Most of the reported values are positive, indicating that price-rent ratios went up in urban relative to suburban areas. For the average MSA, the increase is 6.99%. What this implies depends on the model in question.
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*Pandemic is Transitory*

In the model in which the pandemic is purely transitory, the positive $\Delta\rho d$ implies that urban rent growth is expected to exceed suburban rent growth: $g^u_t - g^s_t > 0$. After the steep decline in urban rents in 2020, urban rent growth is expected to rebound to restore the price-rent ratio to prepandemic level. The large increase in suburban rents will also revert, leading to slower expected rent growth in the suburbs. Columns (10–11) report the urban minus suburban cumulative rent differential, computed from equation (2.6) under assumptions 2 and 3, respectively.

To implement equation (2.6), we need values for $(\rho_d, \rho_s, \rho^/)$. We set $\rho_d = 0.747$. This is the estimated 12-month persistence of annual rent growth rates in the U.S. between 1982 and 2020. It implies a half-life of expected rent shocks of approximately 2.5 years. Note that the AR(1) assumption on expected rents means that a 1% point change in current period expected rent translates into a $(1 - \rho^/\rho_d)^{-1} \approx 3.5\%$ point cumulative change in rents over the current and all future periods (assuming a typical value for $\rho^/$). We set $\rho_s = 0.917$ based on the observed persistence of aggregate annual price-rent ratio. We compute $\rho^/$ from equation (B.1), using the population-weighted mean price-rent ratio for all ZIP codes in the MSA pre-pandemic.

If there is no differential change in urban versus suburban risk premia (Assumption 2), urban rent growth is expected to exceed suburban rent growth by 8.13% points in the average MSA over the next several years cumulatively (column (10)). However, if the urban risk premium temporarily rises by 1% point relative to the suburban risk premium (Assumption 3), then urban rent growth will exceed suburban rent growth by 15.6% cumulatively (column (11)).

There are large differences across MSAs. Los Angeles is expected to see much larger cumulative urban-suburban rent growth between 20.12% (column (10)) and 28.69% (column (11)). This is because the change in the urban-minus-suburban price-rent ratio is much larger (13.41%). Restoring the pre-pandemic urban-suburban price-rent multiples requires large catch-up growth in urban rents. The same is true for Philadelphia, Sacramento, and Charlotte.

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21 We compute the log price-rent ratio for the United States from January 1987 until December 2020 as the log of the Case-Shiller Core Logic National House Price Index minus the log of the CPI Rent of Primary Residence series. We then take the 12-month autocorrelation.
Miami, St Louis, and Baltimore are at the other end of the spectrum with low urban-suburban rent growth expectations (column (10)). Baltimore is unusual in that it has lower price-rent ratios, lower rent growth, and higher risk premia in the urban core than in the suburbs before the pandemic. If the gap between the urban and suburban risk premium rises by a further 1% point during the pandemic (column (11)), urban rent growth must exceed suburban growth by 8.81% to restore the old price-rent ratios.

Appendix Figure B.14 shows the expected rent growth for each ZIP code, which is a declining function of distance from the city center. The transitory model predicts higher urban rent growth in 2021 and beyond.

_Pandemic is Permanent_

In the model where the pandemic is permanent, the interpretation of the price-rent ratio change \( \Delta pd^l \) is quite different. Columns (12) and (13) report the expected urban minus suburban rent growth, as given by equation (2.7) under assumptions 3 and 4, respectively. These columns report an annual growth rate differential (not a cumulative change), but that change is now expected to be permanent.

If risk premia do not change, the average MSA’s price-rent ratio in December 2020 implies permanently higher annual rent growth of 0.61% in urban than in suburban ZIP codes. If the urban-suburban risk premium rises permanently by 1% point, urban rent growth is expected to exceed suburban growth by 1.61% annually. The numbers in columns (12) and (13) differ by exactly 1% point, the assumed difference in urban-suburban risk premia between the two columns.\(^\text{22}\) In sum, the permanent model also expects the rent in urban ZIP codes to grow more strongly than in the suburbs.

\(^\text{22}\)Column (13) can be compared to column (11), after dividing column (11) by about 3.5 (more precisely, multiplying it by \(1 - \rho^l \rho^s\)). Both numbers then express an annual expected rent growth under the assumption that risk premia in urban areas go up by 1% point relative to suburban areas.
The Pulsenomics survey held in February of 2021 finds that 64% of survey respondents believe that working from home represents a temporary shift for the housing market, while 36% believe the shift is permanent. The sample consists of 102 real estate experts from banking, consulting, and academia.\textsuperscript{23} We use this survey evidence to estimate the probability parameter that the change in the housing market is transitory: $\mu = 0.64$. Using the experts’ view on the transitory versus permanent nature of the working from home shift, we can then compute the expected rental growth rate from equation (2.8).

Figure 2.13 summarizes our results for the population-weighted average MSA. We show the evolution of the urban-minus-suburban expected rent growth differential. The red line is for the purely transitory case ($\mu = 1$), the blue line for the purely permanent case ($\mu = 0$), and the orange line for the main, combination case ($\mu = 0.64$). The left panel shows the results assuming no change in urban-minus-suburban risk premia ($\Delta x = 0$), while the right panel shows the case of $\Delta x = 0.01$.

The prediction of an increase in urban relative to suburban rents—an urban rent revival—is robust, as all predicted lines are above zero. In the transitory cases, annual expected rent growth increases strongly initially, about 2.39% points in the left panel and 4.59% points in the right panel, and then slowly reverts back down to pre-pandemic levels. In case the pandemic change is permanent, the rent growth differential jumps up post-pandemic and remains there. The jump is 0.61% in the left and 1.61% in the right panel. For our preferred combination case, the trajectory of expected rent growth naturally lies in between the two extreme cases. Under our preferred assumption on expected returns in the right-hand side panel, the model predicts rent growth in

\textsuperscript{23}Pulsenomics surveys these experts about their house price expectations every quarter. Each survey has additional one-off topics. The question in the 2021.Q1 survey used here is on the topic of shifting housing preferences: “The pandemic and rise of remote work have altered housing needs and preferences, though it is uncertain if these changes will prove to be permanent or temporary. For each of the following, would you say that consumer preferences have shifted permanently, temporarily, or not at all? Full-time work from home in favor of full-time work from company office.” In addition to the working from home question, which we use, there is also a question on “suburban lifestyle in favor of urban lifestyle.” This question received the following responses: 46% permanent and 54% transitory (includes 8% no change).
Notes: This figure shows the evolution of urban minus suburban rent growth pre- and post-pandemic in the cases in which the pandemic is transitory (red) permanent (blue), and combining both regimes (orange). We plot the population weighted average of the MSAs. We consider two cases as in Table 2.3: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$.

2021 for urban ZIP codes that exceeds that in suburban ZIP codes by 3.52% points. In the long-run, urban rent growth exceeds suburban growth by 0.80% points.

Appendix Figure B.18 reports the combination model’s prediction for individual MSAs. There is substantial variation in predicted urban rent growth revival, with large values for Los Angeles, Sacramento, Charlotte, Philadelphia, and Phoenix. Appendix Figure B.19 discusses the various models’ implications for the evolution of price-rent ratios in urban versus suburban ZIP codes. After rising during the pandemic, price-rent ratios reverse back down but remain above pre-pandemic levels with interesting dynamics in our preferred combination case with rising urban risk premia.

2.6 Conclusion

A central paradox of the internet age has been that digital tools enable greater collaboration at further distances, yet have led to more concentrated economic activity in few dense urban areas. We document that the COVID-19 pandemic, and the migration flows it triggered, has partially reversed this trend. The reversal in the premium for urban real estate is particularly strong for rents but also present in house prices. These shifts in economic activity appear to be related to work
from home practices, suggesting that they may persist if employers allow remote work beyond the pandemic. Combining a present-value model with professional forecasters’ opinion on the permanency of work from home, we find that housing markets paint an optimistic picture of urban revival, indicating higher rent growth in urban versus suburban areas for the foreseeable future.

A key benefit to workers of this changing economic geography is access to large and more elastic housing stock at the periphery of cities, thereby alleviating rent burden. However, the results also point to potential problems for local government finances in the wake of the pandemic. Urban centers may confront dwindling populations and lower tax revenue from property and sales in the short and medium run. More dispersed economic activity may offer greater opportunities for areas previously left behind, but potentially at the cost of agglomeration economies built in urban areas. Our results point to important challenges and opportunities in the context of a radically reshaped urban landscape.
Chapter 3: Work From Home and the Office Real Estate Apocalypse

We show remote work led to large drops in lease revenues, occupancy, lease renewal rates, and market rents in the commercial office sector. We revalue New York City office buildings taking into account both the cash flow and discount rate implications of these shocks, and find a 39% decline in long run value. For the U.S., we find a $413 billion value destruction. Higher quality buildings were buffered against these trends due to a flight to quality, while lower quality office is at risk of becoming a stranded asset. These valuation changes have repercussions for local public finances and financial stability.

3.1 Introduction

“Commuting to office work is obsolete. It is now infinitely easier, cheaper and faster to do what the nineteenth century could not do: move information, and with it office work, to where the people are. The tools to do so are already here: the telephone, two-way video, electronic mail, the fax machine, the personal computer, and so on.”

Peter F. Drucker, 1989

The Covid-19 pandemic led to drastic changes in where people work. Physical office occupancy in the major office markets of the U.S. fell from 95% at the end of February 2020 to 10% at the end of March 2020, and has remained depressed ever since, only gradually creeping back to 47%

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1This chapter is based on Gupta, Mittal, and Nieuwerburgh (2022), and is part of the NBER Working Paper Series (#WP 30526). The paper is also cited in multiple news reports, such as Bloomberg, Fortune, Freakonomics Podcast, The Economist, The New York Times, among others. We thank Jonas Peeters, Neel Shah, and Luofeng Zhou for excellent research assistance and CompStak for generously providing data for academic research. We would like to thank Chen Zheng (discussant), Cameron LaPoint (discussant), Jiro Yoshida (discussant), and seminar participants at AREUEA (DC), AREUEA International (Dublin), the USC Macro-Finance Conference, Cornell, Boston Fed, the Chinese University of Hong Kong finance seminar, Michigan Ross, National University of Singapore, Columbia Business School finance seminar, the Remote Work Conference at Stanford, the Urban Economics Association Conference (DC), New York University Stern macro seminar, PUC Chile, the Federal Reserve Board Stress Testing seminar.
by November 2022. In the intervening period, work-from-home (WFH) practices have become more established, with many firms announcing permanent remote or hybrid work arrangements associated with shrinking physical footprints. These shifts in current and projected future office demand have led to concerns that commercial office buildings may become a stranded asset in the wake of disruptions resulting from remote work. Because office assets are often financed with debt which resides on banks’ balance sheets and in Commercial Mortgage-Backed Security (CMBS) portfolios, large declines in value would have consequences for institutional investors and for financial stability.\footnote{Investable commercial real estate assets were worth about $4.7 trillion at the end of 2019, of which office represents the largest component. They make up an important part of the portfolio allocation to “real assets” of a growing number of institutional investors (Goetzmann, Spaenjers, and Nieuwerburgh (2021)). Banks have about $2.4 trillion in commercial real estate loans on their balance sheets as of June 2022 according to Call Report data.} The spatial concentration of office assets in urban central business districts also poses fiscal challenges for local governments, which rely heavily on property taxes levied on commercial real estate to provide public goods and services. A decline in office and adjacent retail real estate valuations may activate a fiscal doom loop that lowers the quality of life for urban residents and worsens the business environment.

In this paper, we ask what these changes in remote work arrangements imply for the value of office buildings. To answer this challenging question, we combine new data with a new asset pricing model. A central model ingredient is uncertainty about future WFH arrangements.

The value of office reflects the expected present discounted value of its cash flows. We begin by analyzing the shock to current cash flows. Using a unique data set from CompStak, we study lease-level data for 105 office markets throughout the United States over the period from January 2000 until May 2022. We document a 16.89 percentage point decrease in lease revenue in real terms between December 2019 and May 2022. Two-thirds of this decline reflects decreases in the quantity of in-force leases. The remainder is accounted for by declines in real rents on in-force leases. The quantity of newly-signed leases in our data set falls from 253.43 million square feet per year just before the pandemic to 59.32 million square feet in May 2022. Rents on newly-signed leases fell by 13.16% in real terms between December 2019 and December 2021 before reversing to pre-pandemic levels by the end of 2021, with meaningful heterogeneity across cities. Because

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\text{\textsuperscript{2}} \text{Investable commercial real estate assets were worth about $4.7 trillion at the end of 2019, of which office represents the largest component. They make up an important part of the portfolio allocation to “real assets” of a growing number of institutional investors (Goetzmann, Spaenjers, and Nieuwerburgh (2021)). Banks have about $2.4 trillion in commercial real estate loans on their balance sheets as of June 2022 according to Call Report data.}\]
a large fraction of leases in-force in early 2020 did not come up for renewal in 2020 and 2021 (61.77% in the U.S., 71.59% in New York), and vacancy rates are already at 30-year highs in several major markets (21.5% in New York in 2022.Q2), rents may not have bottomed out.

We establish a direct connection between firms’ remote work plans, measured either from remote work job postings or from corporate announcements on work schedules, and their actual reductions in leased office space. We find firms that have a larger share of job postings which are remote-amenable, or allow their employees to work more days from home, further reduce their office space demand.

The effects on lease revenue are not uniform across properties. We find evidence of a “flight to quality,” particularly in rents. Higher quality buildings, those that are built more recently and have more amenities (informally called class A+), appear to be faring better. Their rents on newly-signed leases did not fall as much or even went up. This is consistent with the notion that firms need to improve office quality to induce workers to return to the office. In contrast, lower quality office appears to be a more substantially stranded asset, given lower demand, raising questions about whether such assets will ultimately need to be repurposed towards other uses.

Because most of the office stock is not publicly-traded (and this segment is also disproportionate high-quality) and sales of privately-held office properties slowed down dramatically during the pandemic, it is not possible to rely on transaction data to infer the changes that remote work wrought onto office values. To address this challenge, a central contribution of our paper is to build a novel asset pricing model to infer the changing values. Office values reflect expectations of future cash flows and discount rates. The model is a bottom-up valuation tool, adapted to the details of commercial real estate assets. A property is a portfolio of long-term leases. The model features long lease duration, leasing risk, market rent risk, and supply growth risk. We aggregate lease revenues to the property level and subtract costs to arrive at net operating income. The model aggregates so we can compute the value of (a segment of) the office market as a portfolio of office properties. There are two sources of aggregate risk: standard business cycle risk and aggregate uncertainty regarding the state of remote work, with stochastic transitions between a no-WFH and a
WFH state. Rent growth, supply growth, lease renewals, new lease signings, and costs vary across these aggregate states.

Our main calibration exercise is to New York City’s office market. The model matches market rent, supply, and vacancy dynamics in the data. This includes the sharp increase in office vacancy rates between 2020 and 2022. The model’s stochastic discount factor (SDF) is chosen to match the observed risk-free interest rate, the equity risk premium in the stock market (and its fluctuation across recessions and expansions), and the returns on a new WFH risk factor, which we create. The WFH risk factor goes long stocks which support remote work practices (i.e., Zoom) and goes short stocks which are reliant on physical presence (i.e., airlines).

A key parameter that affects the change in office valuations due to remote work is the persistence of WFH practices. We back out this parameter from the (unlevered) stock return on NYC-centric office REITs observed between December 2019 and December 2020. Since REITs predominantly invest in A+ office product, we do so for a separate calibration to the A+ segment of the NYC office market. The model matches the 2020 (unlevered) office return for an annual persistence parameter of 0.818, indicating that office investors believe remote-work practices to be long-lasting. We show that our conclusions are robust to the specific choice of our persistence parameter.

With this parameter in hand, we return to the full NYC office market calibration. We obtain a 44.80% reduction in the value of the entire NYC office stock between December 2019 and December 2020. Simulating the model forward for ten years, we characterize the mean value of the office stock and—just as importantly—the uncertainty around this valuation, which depends on the sequence of shocks that hits the economy. Along the average path, office occupancy stabilizes and the economy returns to the no-WFH state with some probability. These mean-reversion forces push office valuations towards an average office value in 2029 that is about 39.18% below 2019 values. Along paths where the economy remains in the WFH state, office values in 2029 are 59.86% below their 2019 values. Hence, there is substantial uncertainty about future office values, WFH risk, that our approach quantifies.
We repeat the calibration exercise for San Francisco and Austin, the former an example of an office markets that is hit even more by remote work and the latter an example of a market that has been more resilient. Naturally we find larger valuation reductions in the former, compared to NYC, and smaller reductions in the latter. However, both markets see declines, suggesting that spatial reallocation of activity (for example, from New York City to the Sunbelt) is not entirely driving our results.

What do these numbers imply for the aggregate value of the office stock? For NYC, we observe $17.76 billion in annual lease revenue in the CompStak data pre-pandemic and the ratio of office value to lease revenue is 6.02 based on our model. Hence, the value of the NYC office properties in our dataset is $124.43 billion. The short-term value reduction of 44.80% amounts to $55.75 billion, while the longer-term reduction of 39.18% amounts to $48.75 billion. Extrapolating to all properties in the U.S. in our dataset, the $64.86 billion annual leasing revenue results in a $454.34 billion office value before the pandemic using the same 6.02 value-to-lease revenue ratio. We estimate that pandemic-related disruptions around remote work have lowered the value of office buildings observed in our dataset by $203.54 billion in the short run (44.80%) and by $178.01 billion in the long-run (39.18%). Adjusting for incomplete data coverage, the total decline in commercial office valuation in the U.S. is estimated at $484 billion in the short-run and $413.44 billion in the long-run.3

The key takeaway from our analysis is that remote work is shaping up to massively disrupt the value of commercial office real estate in the short and medium term. These findings are informed by our results that firms appear to demand substantially less office space when they adopt remote working practices, and that such practices appear to be persistent. In the long run, firms may discover that the productivity or innovation impact from remote work is worse or better than expected, remote-work technologies may improve further, and cities may repurpose existing office assets to

3Table 3.6 details the coverage of CompStak data for the largest 20 markets, using the inventory data from Cushman & Wakefield as the universe. For these markets, we scale up our value change by the inverse of the market-specific coverage ratio. For the remaining 85 office markets, we divide by a common coverage ratio, chosen to reconcile the aggregate office stock in CompStak (1832.14 million square feet of active leases in our dataset in February 2020) with Cushman & Wakefield’s office stock (5,375 million square feet at the end of 2019).
alternative use. These changes are likely to play out over decades and are beyond the horizon of our analysis.\textsuperscript{4}

**Related Literature.** Our work relates to four literatures. One strain of research has focused on identifying disruptive technological shocks to asset prices. An important topic in this literature has been that of stranded assets: whether innovation or climate change have the potential to transform existing assets into liabilities, with consequences for the creative destruction of economic activity (Gârleanu, Kogan, and Panageas (2012); Kogan and Papanikolaou (2014); Kogan and Papanikolaou (2019); Barnett, Brock, and Hansen (2020); Pástor, Stambaugh, and Taylor (2022)). We contribute to this literature by documenting a novel disruptive shock in the form of remote work, proposing a work-from-home risk factor, and highlighting exposure of urban commercial real estate assets to the WFH factor.

We also relate closely to the rapidly growing literature on the impact of remote work on real estate, surveyed in Van Nieuwerburgh (2023). Rosenthal, Strange, and Urrego (2021) documents a decline in the commercial rent gradient in the city center and transit cities as compared to car-oriented cities with COVID-19. Bartik et al. (2020); Barrero, Bloom, and Davis (2021); Aksoy et al. (2022) present survey data to assess the prevalence of remote work and investigate reasons why working from home is expected to last. Hoesli and Malle (2021) analyze the effect of COVID-19 on commercial real estate in the European markets. Gupta et al. (2021); Brueckner, Kahn, and Lin (2021); Ramani and Bloom (2021); Mondragon and Wieland (2022) study the impact of work from home on residential real estate prices in urban and suburban areas. Cohen, Friedt, and Lautier (2020) shows changes in real estate prices in New York City due to COVID-19.

An important urban economics branch of this literature explores the effects of remote work in quantitative general equilibrium models of labor and real estate markets (Delventhal, Kwon, and Parkhomenko (2022); Davis, Ghent, and Gregory (2021); Li and Su (2021); Gokan et al. (2022)). These models are well-suited for thinking about long-run implications of remote work on city structure, including how office space could be used for alternative purposes. This paper uses

\textsuperscript{4}That said, our model calibration features a reduction in office supply in the WFH state, capturing reduced construction activity and adaptive reuse of office assets in the WFH state.
micro data on office leases to document changes in commercial real estate markets with a rise in remote work, and uses these data as inputs in a new asset pricing model. The finance perspective, which places WFH risk at the core, is a useful complement to the urban economics perspective. An important challenge for future work is to integrate these two approaches.

Finally, our work relates to literature examining commercial real estate as an asset class. Cvijanović, Milcheva, and Minne (2021); Badarinza, Ramadorai, and Shimizu (2022) study the role of investor characteristics in commercial real estate. Geltner (1993) assesses valuation given existing appraised values. A key contribution of our paper to this literature lies in developing a tractable, yet rich bottom-up model of commercial building valuation. The valuation model has broad applicability to study pricing of publicly- and privately-traded assets in different contexts.

The rest of the paper is organized as follows. Section 3.2 overviews changes in the office leasing market during the pandemic, highlighting the contemporaneous losses to lease revenue. Section 3.3 estimates the valuation of office buildings in the context of a structural model, and Section 3.4 highlights the implications for office valuation. Section 3.5 concludes. Appendix C.1 estimates changes to future expected returns in the context of an asset pricing model incorporating work-from-home risk. Appendix C.2 provides model derivations. Appendix C.3 details the calibration algorithm. Appendix C.4 reports additional results from the model. Appendix C.5 contains the calibration details for San Francisco and Austin.

3.2 The Office Market During the Pandemic

3.2.1 Data

In comparison to other real estate markets, such as residential real estate, the market for commercial office buildings is opaque. We combine cash flow and pricing data from both public and private markets in order to understand the valuation of the entire office sector in light of disruptions introduced by the shift to remote work.

Our main data set is CompStak, a data platform where commercial real estate brokers exchange leasing information. The data set contains lease-level transaction data for a large sample of offices.

Our data contain information on the lease, the building, and the tenant. Lease characteristics include: the execution date, lease commencement date, lease expiration date, the starting rent, the rent schedule, free rent period, tenant improvements, the size (in square feet) of the lease, floor(s) of the building, lease type (new lease, extension, expansion), and other lease options. Building characteristics include: building location, building class (A, B, or C), building age, submarket, market. Tenant characteristics include: tenant name, tenant industry (SIC and NAICS code), tenant employees, and tenant ticker (if publicly traded). We use this data to study the evolution of the lease market over the course of the pandemic, in terms of quantities, prices, and contract features.

In public markets, we obtain office REIT return for office REITS included in the National Association of Real Estate Investment Trust (NAREIT) office index for the period 2019–2021.

To measure remote working conditions at the firm level, we use job postings data drawn from Ladders, an online job search service site. The platform focuses on job positions paying in excess of $100,000 a year, and so has high coverage of many remote working positions more commonly represented in high-wage professions. We use this service to track the fraction of job postings which mention fully remote terms at the firm level. This allows us to measure remote working plans by office tenants and connect them to their leasing decisions.

We also measure hybrid work conditions for a sample of 200 firms, chosen from among the firms with the largest presence in our leasing data. We hand-classify working plans (in-person, hybrid, and fully-remote) as well as the number of anticipated days back in the office for these firms.\(^5\)

### 3.2.2 Shock to Leasing Revenue

Figure 3.1 highlights the first component of the valuation shock: the reduction in current leasing revenue. We compute the total annual leasing revenue on all in-force leases each month, excluding

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\(^5\) We used two separate research assistants to hand-classify remote working plans, before having a third assistant reconcile the two classifications into one uniform data set.
subleases to avoid double-counting of revenue. The total value of annualized leasing revenue was $64.86 billion prior to the pandemic in December 2019 (all numbers expressed in December 2021 dollars). Total leasing revenue then experienced a 16.89% decline, falling to $53.90 billion in May 2022 (Panel A). This decline is substantial taking into account the long-term nature of commercial leases. It indicates substantial shifts in leasing activity among those tenants in a position to make a choice about their office space needs.

We decompose this decline in total leasing revenue into its two underlying components: changes in average rents on in-force leases (Panel B) and changes in quantities (Panel C). The average rent is again expressed in real 2021 dollars.

While we observe contractual pricing terms in the CompStak data, lease terms require some discussion. We focus on net effective rents (NER), which augment the standard contract rent schedule (a rent for each month over the course of the lease) with additional provisions including rent concessions (free rent) as well as tenant improvements (work paid for by the landlord). The resulting NER reflects the average rent earned by the landlord, and is the most relevant object in understanding changing market rent dynamics. Annualized net effective rents on in-force leases fell in real terms throughout the pandemic. Most leases in-force during the pandemic were signed before the pandemic and have built-in nominal rent escalation clauses. However, the scheduled rent increases were not large enough to keep pace with inflation, leading to a modest real NER drop on active leases of 5.75%. We also show below that net effective rents on new leases signed during the pandemic fell substantially below pre-Covid rent levels in the first year of the pandemic.

In addition, the quantity of in-force leases (in square feet) also fell substantially during the pandemic (Panel C). The decline is 11.15% between December 2019 and May 2022. This decline reflects (i) difficulties in filling vacant space with new tenants, (ii) lack of lease renewals by existing tenants whose lease is up for renewal, and (iii) renewals for less space than the prior lease. This suggests that understanding the quantity dimension is of utmost importance when it comes to understanding shocks to pandemic cash flows.
Figure 3.1: Current Office Lease Revenues

(A) Total Lease Revenue on In-force Contracts

(B) Average Rent on In-force Contracts

(C) Quantity of In-force Contracts

Notes: Data are sourced from CompStak.
Flight To Quality in Lease Revenue

The decrease in current lease revenue is felt most strongly for lower- than for higher-quality office space. To measure high-quality buildings, we define “A+” properties by isolating leases that are in the top ten percent of NER in each quarter and submarket among all properties that are ranked as Class A by CompStak. We categorize a building that has such a lease as A+ and assume that the A+ status remains for ten years, unless another top-10% lease is signed in that building at which point the ten-year clock resets. The remaining buildings (“Other”) are classes “A-” (A without A+), B, and C. The right panels of Figure 3.1 separate out the two groups, normalizing the statistics for each group at 100 in December of 2019. We see that rent increases are stronger for Class A+ buildings during the pandemic (Panel B), and the decline in active leases is smaller (Panel C). The combination of both of those forces means that total annualized leasing revenues fall by 14.69% for A+ properties versus by 17.79% for the rest of the office universe.

We observe even stronger evidence for differing trends across office space by quality in Figure 3.2, which focuses on New York City (NYC) and Texas, as representative examples of both major and non-major commercial real estate markets. Panels A and B display changes in NER per square foot (sf) on newly-signed leases. The left panels define A+ properties as before. The right panels use an alternative definition of high-quality buildings based on building age: younger buildings are those constructed in or after 2010. Properties defined as A+ sustain rent levels much better in both New York and Texas compared to other properties. Younger buildings even experience sizable rent increases, compared to substantial rent decreases for other properties. This divergence suggests a “flight to quality” in office demand in these markets.

3.2.3 Physical Occupancy, Contractual Occupancy, and Lease Expiration

In Figure 3.3 (Panel A) we highlight the key shift which is the focus of our paper: the sudden drop in physical office presence for white-collar workers. Physical office occupancy is measured from turnstile data provided by Kastle.6 Over the course of the pandemic, about 70% of college-

6The Kastle data cover more than 2,600 buildings in 138 cities.
Figure 3.2: Changes in Office Rents and Occupancy

(A) Net Effective Rent by Quality Segment in NYC

(B) Net Effective Rent by Quality Segment in Texas

(C) Occupancy Rates by Quality Segment in New York City

(D) Occupancy Rates by Quality Segment in Texas
educated workers did some or all of their work from home. In the initial wave of the pandemic, physical office occupancy rates fell to just 20% among the top-10 largest office markets (10% in NYC). Average occupancy recovered to about 30% (20%) by the end of 2020. It saw several more dips as the pandemic intensified in early 2021. The recovery continued in the second half of 2021 to about 40% (35%), before falling sharply due to the rise of the Omicron variant at the end of 2021. The latest data as of early November 2022 show a 47.3% occupancy rate among the largest 10 office markets (46.7% in NYC). With two and a half years of remote work experience, many employers and employees have formed new habits and expectations. Employees have come to like remote work and report being more productive. Employers have revised upward their own longer-run expectations on average employee days in the office (Barrero, Bloom, and Davis (2021); Aksoy et al. (2022)), and have begun to adjust their demand for office space as shown in more detail below.

Figure 3.3: Office Occupancy

These large drops in physical occupancy did not translate into large immediate drops in commercial office cash flows, as shown above. The reason for the delayed and gradual reaction is the staggered nature of commercial leases, highlighted in Figure 3.4. Because most commercial leases are long-term, and not up for immediate renewal, only a fraction of office tenants have had to make active choices about their future office demand so far. Among all in-force leases as of the end of December 2019, only 38.23% came up for renewal in 2020 and 2021 combined. Nearly all of the

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tenants not up for renewal have continued to make rent payments, despite their lack of physical occupancy. When more leases come up for renewal in the future, the office demand of tenants who have made limited use of office space during the pandemic remains highly uncertain and is a crucial determinant of office valuation.

Figure 3.4: Lease Expiration Schedule

Despite the modest share of tenants that have seen lease expirations so far, we already observe drastically higher vacancy rates reflecting lease exits among that sample. The contractual occupancy rate in Manhattan, the country’s largest office market, was at a 30-year low of 78.5% in the second quarter of 2022 (Cushman & Wakefield), as shown in Figure 3.3 (Panel B). Panels C and D of Figure 3.2 plot occupancy rates for NYC and Texas using our CompStak data, scaled to 100 in December 2019. The left panels show that occupancy rates fell for both A+ and lower-quality buildings. The right panels shows that younger buildings, those built after 2010 or after 2015, saw substantially stronger occupancy during the pandemic than older buildings.

Notes: The figure shows percentage of active leases as of December 2019, i.e., pre-pandemic by expiration year (left panel), and percentage of active leases as of December 2021, i.e., post-pandemic by expiration year (right panel). Data are sourced from CompStak.
3.2.4 Impact on Quantities and Prices of New Leases

Pandemic Impact on New Lease Quantities

We next turn to examine the consequences of pandemic-associated shifts in office demand on the number of new leases signed. To do so, we aggregate the total number of new commercial office leases signed in the CompStak data. We observe a dramatic decrease in the quantity of new leases signed, sometimes called absorption in the industry, across both sets of markets in Figure 3.5. The volume of newly signed leases fell from 253.43 million sf per year in the six months before the pandemic to 59.32 million sf per year over the most recent six months. This indicates a substantial drop in office demand from tenants who are actively making space decisions.

Figure 3.5: New Leases Signed

Notes: The graph plots the six month moving average of total square footage of leases signed annually in millions. Data are sourced from CompStak.

\(^7\)In unreported analysis, we find that the changes are similar in major and non-major office markets. The major office markets are: New York City, Philadelphia, Boston, Houston, Dallas, Austin, Nashville, Chicago, Atlanta, Miami, Washington D.C., Denver, Los Angeles, Bay Area, and San Francisco.
**Pandemic Impact on New Lease Duration**

Even when tenants do renew leases, they may not do so under the same set of terms. Figure 3.6 shows that the share of new leases signed that are less than three years in duration increased substantially during the pandemic, to account for almost half of our sample, while the share of leases with a duration more than seven years decreased meaningfully. The shortening of lease duration suggests important shifts in the commercial office market, even conditional on lease renewal. As a result, the coming years 2023–2025 will feature even larger than expected lease expiration from two channels: the pre-scheduled expiration of long-term leases signed before the pandemic, as well as the expiration of short-term leases signed during the pandemic. This is shown in Panel B of Figure 3.4.

*Figure 3.6: Lease Duration Changes*

![Graph showing lease duration changes from 2015 to 2022.](image)

**Notes:** The graph shows percentage of leases signed, less than 3 years in duration (blue line), and percentage of leases signed, greater than 7 years in duration (orange line). Data are sourced from CompStak.

**Pandemic Impact on New Lease Rents**

We next explore the dynamics of net effective rents on new leases. We compute the square-foot weighted average NER (in 2021 dollars). Figure 3.7 shows large changes in real NERs on new
leases signed over the course of the pandemic. Panel A is for all markets and Panel B is for New York City. We provide both a longer-term perspective in the top row and zoom in on the post-2018 period in the bottom row of each panel. Nationally, the NER fell by 13.16% in 2020. Starting in January 2021, the NER on newly-signed leases experienced a sharp reversal with the NER ending up back at its pre-pandemic level at the end of our sample.

The national average NER dynamics could reflect composition effects, either in terms of in the markets in which new leases are being signed or in terms of the types of tenants signing new leases. To control for such selection effects, we remove tenant-industry and geographical fixed effects. Once fixed effects are removed (solid line), both the decline in NER in 2020 and the rebound in 2021 become weaker. Much of the recent rebound in NER in the raw data turns out to be a spatial composition effect.

In NYC, the NER decline on new leases in 2020 is sharper at 15.94%, and the rebound in 2021 and 2022 is much weaker. The measurement in NYC is not sensitive to the removal of tenant and submarket fixed effects.

**Flight to Quality in Building Attributes**

The right panels of Figure 3.7 break down the market-wide NER dynamics by quality segment: A+, A- (all other class A), in addition to B and C units. We focus on the solid lines, which remove fixed effects. Nationally, A+ rents on new leases show resilience, rising modestly between December 2019 and May 2022. Lower-quality office rents, by contrast, see a much steeper decline over the pandemic. In NYC, A+ rents on new leases show stronger declines in 2020, but rebound more sharply in 2021 compared to other market segments. Rents on lower-quality office buildings fall without much of a rebound in 2021.

Figure 3.8 illustrates the flight-to-quality dimension further by plotting the relationship between building age and NER in Panel A for New York and San Francisco leases. The NER is residualized with respect to month, submarket, and tenant fixed effects, and so as to control for shifting geographic or tenant composition. It shows that the rent-quality gradient steepens sub-
Figure 3.7: Net Effective Rent on New Leases

Source: CompStak. All FE includes state, major/non-major market, industry and renewal FEs. Major markets are defined in footnote 7.
stantially for leases signed in March 2020 or later versus before. Rather than sorting buildings by age, Panel B sorts them by their rent rank, where 0.9 indicates the 90\textsuperscript{th} percentile of the NER distribution. Again, we find a strong association between building quality and rents in general in the cross-section of building quality (consistent with the general role for filtering as in Baum-Snow and Rosenthal (2022)), but a steeper gradient after the pandemic. The quality attribute becomes more highly valued after the onset of the pandemic.

Figure 3.8: Building Quality and Changes in Rents

Table 3.1 provides detailed regression results of the relationship between building age and NER. We control for month and submarket fixed effects (column (1)), as well as tenant fixed effects (column (2)), and building fixed effects (column (3)). The specification in column (3) with both tenant and building fixed effects identifies the quality gradient from tenants that sign multiple leases within the same building at different points in time (at different building ages), enabling a precise estimation of the association between age and rents. Each year of aging reduces NERs by $0.067 per sf in that specification. A building that is ten years older has 2% lower rents relative to the average rent of $34 per sf. Our key test is how this relationship changes over the pandemic,
represented as an interaction term in column (4). We observe that interaction of building age and a post-pandemic indicator variable is negative and significant, indicating that young buildings become even more valuable after the pandemic. This specification compares rent outcomes for leases signed in March 2020 and later, relative to leases signed between January 2018 and February 2020. Column (5) uses log NER and log building age, and shows an additional 2.4% point rent elasticity to age. We observe that this association is largely driven by shifts in major markets (columns (6) and (7)), and is particularly large in New York and San Francisco (column (8)).

Table 3.1: Building Quality and Rent

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Building Age (Yrs)</td>
<td>-0.101***</td>
<td>-0.070***</td>
<td>-0.067**</td>
<td>-0.083***</td>
<td>-0.088***</td>
<td>-0.066***</td>
<td>-0.050***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.011)</td>
<td>(0.030)</td>
<td>(0.015)</td>
<td>(0.016)</td>
<td>(0.014)</td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>Building Age × Post Pandemic</td>
<td>-0.042***</td>
<td>-0.005</td>
<td>-0.001</td>
<td>-0.127***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.031)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Building Age</td>
<td>-0.084***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Building Age × Post Pandemic</td>
<td>-0.024***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age × Post × Major Market</td>
<td>-0.044***</td>
<td>-0.020**</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.009)</td>
<td></td>
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<td></td>
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<td></td>
</tr>
</tbody>
</table>

| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Submarket FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Tenant FE | No | Yes | Yes | No | No | No | Yes | Yes |
| Building FE | No | No | Yes | No | No | No | No | No |
| SF+NYC | 374,262 | 207,764 | 196,430 | 93,322 | 93,328 | 93,322 | 37,272 | 8,128 |

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

This table shows the relationship between firm quality attributes and rent gradients over the pandemic. The left hand side variable is rents in 2021 dollars, except in column (5) in which the dependent variable is log(rents). The right hand controls always include the month of lease commencement and submarket fixed effects. Additional controls include a fixed effect for tenant identity (not available for all leases), as well as a fixed effect for the building. The sample includes all years for columns (1)–(3), and subsets to leases signed from 2018–2021 for columns (4)–(8). Column (8) additionally subsets to San Francisco and New York City. To illustrate the changing premium on quality, we introduce an interaction with post pandemic from column (4), defined as the time period from March 2020 and afterwards. Major markets are defined in footnote 7. Standard errors are double clustered at the month of lease commencement and submarket level.
3.2.5 Connecting Remote Work and Office Demand

*Fully Remote Workers*

Office demand was greatly impacted over the course of the coronavirus pandemic due to the health risks of in-person activity. Businesses invested in remote-working technologies, and both firms and employees become accustomed to new practices of working from home. To the extent that these reflect durable shifts in worker preference and are accommodated by firms, we expect to see ongoing reductions in office demand as a consequence. In contrast, if remote work was mostly a response to pandemic health concerns, a strong rebound seems more likely.

To illustrate shifting firm space demands during the pandemic, Figure 3.9 plots the relationship between the change in leased space between December 2019 and May 2022 by measuring the change in space at the tenant-level (y-axis) against tenant size, as measured by the log of total sf of active leases before the pandemic (x-axis). We estimate a strongly positive relationship (blue line), which suggests that the decline in tenant space demand is dominated by smaller firms. This is consistent with the idea that small firms are more likely to be financially constrained (Beck, Demirgüç-Kunt, and Maksimovic (2005)), and hence more sensitive to the cost of commercial leases and more likely to adopt remote work.

*Job Postings*

In order to connect the changes in office demand over the course of the pandemic to shifts in remote work more directly, we conduct two exercises. First, we use job posting data from Ladders which allow us to measure the fraction of a firm’s job listings that are for fully-remote positions.\(^8\) We then estimate the relationship between the change in office demand, measured as the percentage change in active lease space in square feet normalized by employment growth since January 2020, and the fraction of job postings that are remote. Tenants will have a more negative change in office demand if they do not renew leases that come up for renewal during the pandemic, if they renew

---

\(^8\)The Ladders data contains a flag indicating whether the position is remote or not.
Figure 3.9: Change in Firm Office Demand and Size

Notes: This graph shows the relationship between firm office demand and size. For each tenant in the CompStak data, we measure their total square footage leased in December 2019, and in May 2022. A measure of 100% indicates the tenant has retained the same amount of space; a higher number indicates tenant expansion and a smaller number suggests space reductions. We plot this measure, with one dot per tenant, against the total space demand for that tenant before the pandemic (the log active square feet in December 2019). The blue line is the linear best fit relationship indicating that smaller firms were more likely to cut down on space.

and take less space, or if they do not expand space in proportion to their total number of employees. We merge job postings and tenant data for 135 large tenants.

Table 3.2 reports the results. The change in office demand is measured over various periods ranging from the last 3 to the last 24 months (relative to the time of data collection in February 2022). We find a significant negative relationship at all horizons. Our results suggest that firms that express a greater remote work preference in job listings have lower demand for office space. A 10% point increase in the share of remote job postings lowers office demand by 3.9–4.9% points. This result is consistent with the idea that durable shifts in remote work are changing the demand for office space.

Hybrid Work

Second, we connect office demand to firms’ remote work schedules. While many employers have shifted to rely more on fully-remote workers, a large fraction of employers have instead moved to hybrid work (Bloom, Han, and Liang (2022)). Employees are expected to return to the office for some number of days in the week. The implications of hybrid work for office demand
are less clear than for fully-remote positions because firms will still require an office presence. That said, firms may have the ability to stagger staff to come into the office on different days or rearrange the workspace to use it more efficiently (through the use of techniques such as hot-desking, hotelsing, office neighborhoods, and perhaps with the assistance of software).

Table 3.2: Remote Listings and Office Demand

<table>
<thead>
<tr>
<th></th>
<th>(1) (\Delta) Space</th>
<th>(2) (\Delta) Space</th>
<th>(3) (\Delta) Space</th>
</tr>
</thead>
<tbody>
<tr>
<td>Remote Listings (3 months)</td>
<td>-0.392** (-2.41)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Remote Listings (12 months)</td>
<td>-0.492** (-2.46)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Remote Listings (24 months)</td>
<td></td>
<td>-0.468** (-2.01)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.0123 (-0.61)</td>
<td>-0.0106 (-0.52)</td>
<td>-0.0156 (-0.77)</td>
</tr>
<tr>
<td>Observations</td>
<td>135</td>
<td>135</td>
<td>135</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.042</td>
<td>0.044</td>
<td>0.030</td>
</tr>
</tbody>
</table>

Notes: \(t\) statistics in parentheses.
\* \(p < 0.10\), \*\* \(p < 0.05\), \*\*\* \(p < 0.01\)

The dependent variable, \(\Delta\) Space, is constructed from CompStak and defined as the square feet (sf) of leases executed post-pandemic minus the positive part of the difference between sf of leases expired post-pandemic and sf of leases commenced post-pandemic, and normalized by pre-pandemic active sf. The independent variables measure the ratio of remote job postings for a specific tenant within a time window since we downloaded the data snapshot from Ladders in February 2022. More specifically, we look at December 2021 to February 2022, January 2021 to February 2022 and January 2020 to Feb 2022 and check the ratio of tenants’ remote jobs over their total job postings.

To examine the role of hybrid work on office demand, we hand-classify the remote working policies for 200 of the largest tenants. We classify firms into whether their back-to-office plans envision fully in-person activities, hybrid work (some number of days back in the office), or fully-remote based on public press releases and other public statements. For these firms, we also classify the number of days anticipated back in the office. While return-to-office plans remain in flux, our classification provides an estimate of firms’ expected office plans around the time that they make their space decisions.

The left panel of Figure 3.10 shows that hybrid work is strongly associated with lower office space demand. Firm-level office demand drops by 12.5% for hybrid firms, while firms announcing that workers must return in-person see only minimal change in space demand (this decline is statistically significant in a regression). The decline in space for firms announcing a fully-remote future
show the largest decline in office demand, a 16.2% decline in square footage. The latter decline is not even larger because tenants have in-place lease commitments.

Figure 3.10: Hybrid Work and Office Demand

Notes: This figure plots the relationship between firm space demand and stated back-to-work office plans. We measure firm space demand, as elsewhere in the paper, by comparing the firm’s total leased square footage in May 2022 against the amount pre-pandemic in December 2019. We then calculate the firm’s back to office plans by classifying the publicly stated policies as of Summer 2022 for the 200 top firms based on overall space utilization. We sort these into plans that are: fully in person, hybrid (i.e., some full-time requirement), and fully remote. We also assess how many days a week the firm anticipates workers being back in the office: 0 (fully remote positions), 1–3 days/week, and 4–5 days a week (including fully in person requirements).

We observe similar results when comparing the number of days that firms anticipate returning back to the office in the right panel. Fully-remote firms (i.e., those that are anticipating zero days required back in the office) have the largest decline in office demand, while firms anticipating 4–5 days back in the office have the smallest. Firms with 1–3 days/week on-site requirement lie in between those two extremes.

Combined, our results show that office space demand has declined considerably over the course of the pandemic and that changes in remote work policies appear to be driving this trend. Firms with more fully-remote positions, or fully-remote work schedules experience the largest declines in office demand. However, decreases in office demand are still substantial among firms with a hybrid back-to-office plan. These results suggest that even hybrid work plans pose major disruption to aggregate office demand, with significant implications for aggregate office values.
3.3 Office Valuation Model

How do changes in remote work and the accompanying changes in office rent revenues affect the value of office buildings? To answer this important question, we turn to a structural valuation model. As in any valuation, we focus on cash flows and discount rates. Conceptually, the value of a building (or portfolio of buildings or the market overall) is the expected present discounted value of rent revenues $R_{t+j}$ minus expenditures $C_{t+j}$:

$$V_t = E_t \left[ \sum_{j=1}^{\infty} M_{t,t+j} (R_{t+j} - C_{t+j}) \right] = E_t \left[ \sum_{j=1}^{\infty} M_{t,t+j} R_{t+j} \right] - E_t \left[ \sum_{j=1}^{\infty} M_{t,t+j} C_{t+j} \right]$$

$$= V_t^R - V_t^C$$

(3.1)

where $M_{t,t+j}$ is the cumulative stochastic discount factor (SDF) between $t$ and $t+j$. $V_t$ is an end-of-period (ex-dividend) price. By value additivity, the value of the building is the difference between the value of the (positive) rents minus the value of the (positive) costs. This gets around the issue that the difference between revenues and costs (before-tax net cash flow) can be negative.

Several real-world complications arise regarding a property’s cash flows which make this valuation more difficult than the valuation of, say, a stock’s dividend stream. Each building is a portfolio of leases with different lease terms and maturity dates. Physically identical buildings therefore have different valuations as a result of different lease structures in place. The leases are finite, but there is additional rental revenue after the leases mature. After some initial vacancy, tenant improvements, and concessions (e.g., free rent) the space will be released at the market rent. Furthermore, the building may not be fully leased, in which case vacancy creates cash flow shortfalls. Hence, the key sources of risk are vacancy risk and market rental risk. On the cost side, the operating expenses including the reserve account to provision for regular capital expenditure or maintenance. A part of the costs is fixed, while another part is variable (with occupancy). Costs also include leasing commissions, which are different for new leases and lease renewals. Finally, there is the risk of supply growth.
The model we propose includes most of these real world features in a tractable way. It can be used to value an individual building, or a (sub-)market, which is a portfolio of buildings. The full derivation of the model is in Appendix C.2. This model should be useful for valuing income-generating properties in any sector or location. Section 3.3.3 describes the calibration of the model, which will focus on the New York City office market.

### 3.3.1 Modeling Revenues

The central challenge in modeling leases is incorporating the process of expiration and lease renewal, at potentially different lease rates. This is important because commercial leases are long-term in nature, but much shorter in duration than the expected life of the building. In our model, leases come due in the current period with probability $\chi$. Under the law of large numbers, $\chi$ is also the share of all leases coming due in a given period in that building/market. The random arrival of lease expiration absolves us from having to keep track of the history of past lease executions. Under this assumption, we only need two state variables to describe the evolution of rental revenues in a building/market: $\hat{Q}_t^O$ and $\hat{R}_t^O$.

Let $Q_t^O$ be the occupied space (in square feet) in a building/market at the end of period $t$ and $Q_t^V$ be the vacant space in a building/market at the end of period $t$. If $\bar{Q}_t$ is the total size of the building/market, then $Q_t^V = \bar{Q}_t - Q_t^O$. The law of motion for occupied space in a building/market is:

$$Q_{t+1}^O = \min \left\{ Q_t^O (1 - \chi) + Q_t^O \chi s_{t+1}^O (z') + (Q_t - Q_t^O) s_{t+1}^V (z') , \bar{Q}_{t+1} \right\}.$$  

The first term denotes the space that was occupied at the end of last period which is not up for renewal. The second term denotes the space that was up for renewal and is renewed for the same or for less space. Here, $0 \leq s_{t+1}^O (z') \leq 1$ is the share of office space that was up for renewal which is being renewed in period $t + 1$. This is a stochastic process whose realized value depends on the state of the world $z'$ in period $t + 1$. It combines the extensive margin of renewal (the share of space that gets renewed versus not-renewed) and the intensive margin of renewal (the share of space in square feet which is renewed conditional on renewal). The third term denotes space that
was vacant at the end of last period and is being newly rented. The stochastic process \( 0 \leq s_{t+1}^V(z') \) is the share of office space that was vacant which is being newly rented out in period \( t + 1 \) if period \( t + 1 \) is in state \( z' \). This term includes the part of lease expansions that exceeds the original space (renewals for more space). This share is not bounded from above by 1, to allow for growth in a building/market due to changes in the supply. The minimum operator guarantees that space occupancy in a building/market is weakly below available supply. It will not be binding in our calibration.

The growth in available space in a building/market is a stochastic process which depends on the model regime:

\[
\frac{\bar{Q}_{t+1}}{\bar{Q}_t} - 1 = \eta_{t+1}(z').
\]

Growth reflects new construction (renovation of a building that adds floor space or new construction in a market) net of depreciation.

We define the scaled state variable \( \hat{Q}_t^O \):

\[
\hat{Q}_t^O = \frac{Q_t^O}{\bar{Q}_t}
\]

with the law of motion:

\[
\hat{Q}_{t+1}^O(\hat{Q}_t^O, z') = \min \left\{ \frac{\hat{Q}_t^O (1 - \chi) + \hat{Q}_t^O \chi s_{t+1}^O(z') + (1 - \hat{Q}_t^O) s_{t+1}^V(z')}{1 + \eta_{t+1}(z')}, 1 \right\}. \tag{3.2}
\]

The rent revenue in a building/market in period \( t + 1 \) takes the following form:

\[
Rev_{t+1} = Q_t^O (1 - \chi) R_t^O + \left[ Q_t^O \chi s_{t+1}^O(z') + (\bar{Q}_t - Q_t^O) s_{t+1}^V(z') \right] R_{t+1}^m
\]

in which \( R_t^O \) is the average net effective rent per square foot on existing leases and \( R_{t+1}^m \) is the market’s net effective rent (NER) per square foot on newly executed leases. The net effective rent incorporates concessions (free rent) and tenant improvements. We assume that all new leases are signed at the market NER. The rent on existing leases is a geometrically-decaying weighted
average of all past market rents, where the weights capture the shares of outstanding leases signed in each of the prior periods:

$$R_t^O = \chi \sum_{k=0}^{\infty} (1 - \chi)^k R_{t-k}^m$$

The law of motion for this second state variable is given by:

$$R_{t+1}^O = (1 - \chi)R_t^O + \chi R_{t+1}^m$$

We define the state variable \( \hat{R}_t^O \):

$$\hat{R}_t^O = \frac{R_t^O}{R_t^m}.$$  

The growth rate of the market’s NER per square foot is a stochastic process: its value depends on the aggregate state realization \( z' \) in period \( t + 1 \):

$$\frac{R_{t+1}^m}{R_t^m} - 1 = \epsilon_{t+1}(z')$$

The law of motion for the scaled state variable becomes:

$$\hat{R}_{t+1}^O (\hat{R}_t^O, z') = \frac{1 - \chi}{1 + \epsilon_{t+1}(z')} \hat{R}_t^O + \chi$$  \hspace{1cm} (3.3)

We can now rewrite rent revenue as a function of the scaled state variables. The rent revenue in a building/market in period \( t + 1 \) takes the following form:

$$Rev_{t+1} = \bar{Q}_t R_t^m \left\{ (1 - \chi)\hat{Q}_t^O \hat{R}_t^O + \left[ \hat{Q}_t^O \hat{Q}_t^O s^O (z') + (1 - \hat{Q}_t^O) s^V (z') \right] (1 + \epsilon(z')) \right\}$$

Define potential rent as the rent revenue based on full occupancy at the prevailing market rent:
\( \overline{Q}_i R_i^m \). Denote the rent revenue scaled by last period’s potential rent with a hat:

\[
\overline{\text{Rev}}_{t+1}(\overline{Q}_t^O, \overline{R}_t^O, z') = \frac{\text{Rev}_{t+1}}{\overline{Q}_i R_i^m}
= (1 - \chi) \overline{Q}_t^O \overline{R}_t^O + \left[ \overline{Q}_t^O \chi s^O(z') + (1 - \overline{Q}_t^O) s^V(z') \right] (1 + \epsilon(z'))
\]

Recall the expected present discounted value (PDV) of lease revenues \( V_i^R \):

\[
V_i^R = E_t \left[ \sum_{j=1}^{\infty} M_{t+j} \text{Rev}_{t+j} \right]
\]

Scale this price by potential rent to obtain a price-dividend ratio:

\[
\hat{V}_i^R = \frac{V_i^R}{\overline{Q}_i R_i^m}
\]

The price-dividend ratio of the lease revenue claim solves the Bellman equation:

\[
\hat{V}_i^R (\overline{Q}_i^O, \overline{R}_i^O, z) = \sum_{z'} \pi(z'|z) M(z'|z) \left[ \overline{\text{Rev}}_{t+1}(\overline{Q}_t^O, \overline{R}_t^O, z') + (1 + \eta(z'))(1 + \epsilon(z')) \hat{V}_i^R(\overline{Q}_{t+1}^O, \overline{R}_{t+1}^O, z') \right]
\]

subject to the laws of motion for the scaled state variables (3.2) and (3.3).

### 3.3.2 Modeling Costs

On the cost side, there are three types of costs: operating expenditures, capital expenditures, and leasing commissions. Note that tenant improvements and concessions (free rent) are already reflected on the revenue side since we consider net effective rent as our rent concept.

We fold the per-period equivalent of capital expenditures into the operating expenses, a common practice (the capital reserve account). These per-period capital expenditures are independent of building occupancy. Other operating costs that are independent of occupancy are: property insurance, property taxes, and the fixed part of utilities and maintenance. We refer to these combined fixed costs per square foot as \( C_i^{fix} \). The presence of fixed costs acts as operational leverage to
the asset. Utilities and maintenance also contain a variable component that depends on building occupancy. Variable costs per square foot are denoted as $C_{i}^{var}$. Finally, leasing commissions (or broker fees) capture costs associated with bringing in new tenants. When a lease expires, leasing commissions are higher for new leases than for renewals: $LC_N > LC_R$. Commissions are variable costs, proportional to the first-year rental revenue from the lease.

Adding the costs associated with fixed and variable expenses, along with broker commissions, yields an expression for total building costs:

$$Cost_{t+1} = C_{t+1}^{fix}(z')\overline{Q} + Q_t^O C_{t+1}^{var}(z') + \left[ Q_t^O \times s_t^O(z') LC_{t+1}^R(z') + (\overline{Q}_t - Q_t^O) s_{t+1}^V(z') LC_{t+1}^N(z') \right] R_{t+1}^m.$$  

We scale costs by lagged potential rent:

$$\overline{Cost}_{t+1} = \frac{Cost_{t+1}}{Q_t R_t^m} = c_{t+1}^{fix}(z') + Q_t^O c_{t+1}^{var}(z') + \left[ Q_t^O \times s_t^O(z') LC_{t+1}^R(z') + (1 - Q_t^O) s_{t+1}^V(z') LC_{t+1}^N(z') \right] (1 + \epsilon(z'))$$

where cost per square foot to market rent per square foot ratios are defined as:

$$c_{t+1}^{fix}(z') = \frac{C_{t+1}^{fix}(z')}{R_t^m} \text{ and } c_{t+1}^{var}(z') = \frac{C_{t+1}^{var}(z')}{R_t^m}.$$  

Note that $\overline{Cost}_{t+1}$ only depends on $\overline{Q}_t^O$ and on $z'$, not on $R_t^O$.

Recall the expected PDV of costs $V_t^C$:

$$V_t^C = E_t \left[ \sum_{j=1}^{\infty} M_{t,t+j} Cost_{t+j} \right].$$

We scale this price by potential rent to obtain a price-dividend ratio:

$$\widehat{V}_t^C = \frac{V_t^C}{Q_t R_t^m}.$$  

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The price-dividend ratio of the building cost claim solves the Bellman equation:

\[
\widehat{V}_t^C(Q_t^O, z) = \sum_{z'} \pi(z'|z)M(z'|z) \left\{ \widehat{Cost}_{t+1}(Q_{t+1}^O, z') + (1 + \eta(z'))(1 + \epsilon(z'))\widehat{V}_{t+1}^C(Q_{t+1}^O, z') \right\} \\
\text{(3.5)}
\]

subject to the law of motion for the scaled state variable in (3.2).

Bellman equations (3.4) and (3.5) have closed-form solutions spelled out in Appendix C.2.

### 3.3.3 Calibration

Since we are interested in understanding how the value of office is affected by remote work, we want to calibrate the model to the entire stock of office. While risk and return are likely to vary across space, we focus here on New York City: America’s largest office market. One key parameter will be identified from the A+ segment of the NYC office market, so we also need a calibration for that segment of the NYC office market. We also repeat the calibration for two more cities: San Francisco and Austin. The former is affected even more severely by remote work than NYC, while the latter is affected less severely.

**States and State Transition Probabilities**

The state variable \( z \) follows a Markov Chain which can take on four values: expansion (E), recession (R), WFH expansion (WFH-E), WFH recession (WFH-R). Here, WFH stands for a world where a lot of work is done remotely or in hybrid format. Before 2020, the world was oscillating between the E and R states.\(^9\)

The model is calibrated at an annual frequency. We decompose the \( 4 \times 4 \) annual state transition probability matrix as the Kronecker product of two \( 2 \times 2 \) transition probabilities. The first matrix governs the dynamics between expansions and recessions. The second one governs the dynamics

\(^9\)We can think of the two non-WFH states as states where there was a small amount of remote work. American Time Use Survey data for 2017 put the fraction of remote work at around 5%.
between no-WFH and WFH states. These two components are assumed to be independent:

\[ \pi(z'|z) = \pi^{BC}(z'|z) \otimes \pi^{WFH}(z'|z). \]

We calibrate expansions and recessions to the observed frequency of NBER recessions in the 1926–2019 data, and the average length of a recession. Recessions are shorter-lived than expansions. This pins down the \(2 \times 2\) matrix \(\pi^{BC}(z'|z)\).

\[
\pi_{BC} = \begin{bmatrix}
E & R \\
0.877 & 0.123 \\
0.581 & 0.419
\end{bmatrix}
\]

The WFH transition matrix is a key object in our valuation exercise. The no-WFH state captures an environment in which remote work is rare, while the WFH state captures an environment in which remote work is common. We set the probability of entering in the WFH state from the no-WFH state equal to \(q = 5\%\), to capture the idea that a transition to mass adoption of remote work was unlikely before 2020. The second parameter is the probability of remaining in the WFH state conditional on having entered it, which we label \(p\). The latter governs the persistence of remote work, and it is a key parameter of interest in the paper. We will infer the value of \(p\) from the observed change in class A+ office valuations at the onset of the pandemic, as measured from office REIT data, and perform robustness with respect to this parameter. As explained in detail below, this calibration delivers \(p = 0.818\). These two parameters pin down \(\pi^{WFH}(z'|z)\):

\[
\pi_{WFH} = \begin{bmatrix}
\text{No WFH} & \text{WFH} \\
1 - q & q \\
1 - p & p
\end{bmatrix} = \begin{bmatrix}
\text{No WFH} & \text{WFH} \\
0.950 & 0.050 \\
0.182 & 0.818
\end{bmatrix}
\]
State Prices

The one-period SDF takes the form $M(z'|z)$. We decompose this SDF into a pre-WFH SDF and a WFH shifter:

$$M(z'|z) = M^{BC}(z'|z) \otimes M^{WFH}(z'|z).$$

We choose $M^{BC}(z'|z)$ to match the risk-free rate and the equity risk premium in both expansions and recessions. First, we match the risk-free rate, conditional on being in a given state:

$$R^f_i(z) = \left( \sum_{z'} \pi^{BC}(z'|z)M^{BC}(z'|z) \right)^{-1}.$$

We average the observed 3-month T-bill rate (in excess of inflation) in expansions and recessions using pre-2020 data. Second, we match the average return on equity conditional on each pair $(z, z')$. That is, we want the conditional Euler equations for the aggregate stock market return $Ret^{mkt}$ be satisfied for each state $z = E, R$:

$$1 = \left( \sum_{z'} \pi^{BC}(z'|z)M^{BC}(z'|z)Ret^{mkt}(z'|z) \right).$$

Combined, the equations for the risk-free rate and the equity return provide four equations in four unknowns, and hence pin down $M^{BC}(z'|z)$:

$$M^{BC} = \begin{bmatrix} E & R \\ E & 0.761 & 2.639 \\ R & 0.262 & 1.917 \end{bmatrix}$$

The model matches the observed long-term average real risk-free rate of 1.5%. It implies a higher real risk-free rate in recessions than in expansions. The model also matches the historical average equity return of 9.5%. The equity risk premium is 8.0% unconditionally, and substantially higher in recessions (13.8%) than in expansions (6.9%).

The SDF component $M^{WFH}(z'|z)$ governs how the risk associated with working from home is priced. It is chosen to price the returns on a portfolio of stocks that goes long companies that
benefit from remote work and short companies that are exposed to remote work. We exclude real estate stocks from the portfolio on purpose. Appendix C.1.2 contains the details of the WFH factor construction. We call this portfolio the WFH equity factor.

We use data from the period December 2014–December 2019 to measure the conditional expected return $\text{Ret}^{WFH}(z'=\text{no WFH}|z=\text{No WFH})$. The WFH equity factor is exposed to stock and bond market risk, as captured by the first two terms below, as well as to WFH risk, as captured by the last term:

$$\text{Ret}^{WFH}(z'=\text{No WFH}|z=\text{No WFH}) = \beta^{mkt} \lambda^{mkt} + \beta^{bond} \lambda^{bond} + \lambda^{WFH}.$$

We estimate the (conditional) stock and bond betas in the December 2014–December 2019 period. Appendices C.1.4 and C.1.5 show how we pin down the (conditional) market prices of risk for the WFH equity risk factor, and for the stock and bond risk factors, respectively. Given our value of $\lambda^{WFH} = -7.0\%$, we find $\text{Ret}^{WFH}(z'=\text{no WFH}|z=\text{No WFH}) = -6.42\%$.

We use the data from December 2019 to December 2020 to measure the conditional expected return $\text{Ret}^{WFH}(z'=\text{WFH}|z=\text{No WFH})$. Since we only observe one such transition in our sample, we are forced to take this simpler approach. This results in $\text{Ret}^{WFH}(z'=\text{WFH}|z=\text{No WFH}) = 30.84\%$.

Given that we have no data on the transition from the WFH to the no-WFH state and only 1.5 annual observations on the return conditional on remaining in the WFH state, we opt to assume instead that the second row of $M^{WFH}$, conditional on $z = \text{No WFH}$, is equal to the first row, conditional on $z = \text{No WFH}$.

We normalize the SDF entry $M^{WFH}(\text{No WFH}|\text{No WFH}) = 1$. This then leaves us with one equation in one unknown. We set $M^{WFH}(\text{WFH}|\text{No WFH})$ to price the WFH equity risk factor return correctly for $z = \text{No WFH}$:

$$1 = \left( \sum_{z'} \pi^{WFH}(z'|z) M^{WFH}(z'|z) \text{Ret}^{WFH}(z'|z) \right).$$
Finally, since we want the risk-free rate to be fully determined by $M^{BC}(z'|z)$ and unaffected by $M^{WFH}$, we scale each row of $M^{WFH, unscaled}$ such that $E[M^{WFH}|z]$ is equal to 1 for each state $z$:

$$
M^{WFH, unscaled} = \begin{bmatrix}
    1 & 1.696 \\
    1 & 1.696 \\
\end{bmatrix}, \quad M^{WFH} = \begin{bmatrix}
    0.966 & 1.639 \\
    0.627 & 1.080 \\
\end{bmatrix}
$$

The model considers the WFH state (second column) to be a worse state of the world—with a higher market price of risk—as the no-WFH state (first column). Assets such as offices, that have lower returns in that state of the world, are therefore riskier.

In sum, the asset pricing model pins down the risk-free rate and contains two priced aggregate risk factors: an equity market factor and a remote work factor.

**Office Cash Flows for All NYC**

Since we are interested in valuing the entire commercial office stock in New York City (the market), our main calibration is for the entire office stock. Below, we also consider a second calibration to the A+ segment, as well as separate calibrations for other office markets. The calibration algorithm is detailed in Appendix C.3.

We set the lease expiration parameter at $\chi = 0.14$. This delivers a lease duration of 7.40 years, matching the CompStak average office lease term in the New York City data. Table 3.3 lists the remaining parameters, which vary by state.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Symbol</th>
<th>E</th>
<th>R</th>
<th>WFH-E</th>
<th>WFH-R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market NER growth</td>
<td>$\epsilon$</td>
<td>0.0544</td>
<td>-0.1251</td>
<td>0.0334</td>
<td>-0.1699</td>
</tr>
<tr>
<td>Supply growth</td>
<td>$\eta$</td>
<td>-0.0152</td>
<td>-0.0158</td>
<td>-0.0407</td>
<td>-0.0413</td>
</tr>
<tr>
<td>Lease renewal share</td>
<td>$s^O$</td>
<td>0.8259</td>
<td>0.2897</td>
<td>0.2748</td>
<td>0.0964</td>
</tr>
<tr>
<td>New leasing share</td>
<td>$s^V$</td>
<td>0.1838</td>
<td>0.3350</td>
<td>0.0612</td>
<td>0.1115</td>
</tr>
<tr>
<td>Fixed cost/rent ratio</td>
<td>$c^{fix}$</td>
<td>0.2000</td>
<td>0.2000</td>
<td>0.2000</td>
<td>0.2000</td>
</tr>
<tr>
<td>Variable cost/rent ratio</td>
<td>$c^{var}$</td>
<td>0.2300</td>
<td>0.2300</td>
<td>0.2300</td>
<td>0.2300</td>
</tr>
<tr>
<td>Leasing commission new</td>
<td>$LC^N$</td>
<td>0.3000</td>
<td>0.3000</td>
<td>0.2400</td>
<td>0.2400</td>
</tr>
<tr>
<td>Leasing commission renewals</td>
<td>$LC^R$</td>
<td>0.1500</td>
<td>0.1500</td>
<td>0.1200</td>
<td>0.1200</td>
</tr>
</tbody>
</table>

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Market NER growth $\epsilon$ in expansions and recessions comes from the January 2000 to December 2019 CompStak data.\(^{10}\) NER is strongly pro-cyclical. Market NER growth in the remote work state comes from the December 2019 to May 2022 CompStak data. Market NER growth was -16.99\% from December 2019 to December 2020 (a WFH-R episode), and +3.34\% per year from December 2020 to May 2022 (1.5 WFH-E years).

Supply growth $\eta(z)$ incorporates new construction net of depreciation and reductions in office space due to conversion to alternative use. The values for supply growth for expansion and recession periods are calculated from CompStak based on the year of construction of all office buildings. New construction is 1.18\% in expansions and 1.12\% in recessions. We subtract a 2.70\% depreciation rate, a realistic number for office property, from the new construction numbers to arrive at the net supply growth $\eta$ reported in the table.\(^{11}\) Supply growth is acyclical because of the long construction lags for office properties.

The values for supply growth in WFH-R and WFH-E periods are calculated by down-scaling E and R supply growth by a fixed amount $\Delta \eta$. The value for $\Delta \eta$ is set such that the model has long-run growth in potential gross rent of zero, given all other parameters. This keeps the model stationary. The calibration has the intuitive feature that supply growth is much lower in the remote work states compared to the no-WFH states, capturing the response of developers to the reduced demand for office as well as conversion of office to alternative uses such as housing.

The parameters $s^O(E), s^O(R), s^V(E), s^V(R)$ govern office demand across the business cycle in the non-WFH states. We pin down these four parameters to match four moments of the NYC contractual vacancy rate over the period 1987.Q1–2019.Q4, plotted in Panel B of Figure 3.3. Those moments are the mean, the standard deviation, the maximum, and the minimum. The resulting lease renewal share for existing leases that are up for renewal, $s^O$, is strongly pro-cyclical. The new leasing share for vacant space, $s^V$, is counter-cyclical, simply because there is much less

---

\(^{10}\)Since NBER business cycles in this period (and before) are shorter than commercial real estate (CRE) leasing cycles, we use the latter to determine the values for annual NER growth in expansions and recessions. Strict adherence to NBER dates would result in office NER growth that is far too similar across expansions and recessions, and make the large fluctuations in rent growth observed in the data highly unlikely events from the perspective of the model.

\(^{11}\)Our depreciation estimate corresponds closely to the 39 years of allowable depreciation expense for non-residential commercial real estate assets for tax purposes.
vacant space available for lease in expansions. This calibration ensures that our model matches both the average vacancy rate of NYC office as well as the amplitude of the leasing cycle, which reflects cyclical tenant demand for office.

The parameters $s^O$ and $s^V$ in the WFH states are assumed to be proportional to their no-WFH counterparts:

$$s^i_{z_{WFH}} = \delta \cdot s^i_z, \quad z = E, R, \quad i = O, V. \quad (3.6)$$

We estimate $\delta$ to best fit the dynamics of the office occupancy rate over the nine quarters from 2020.Q1–2022.Q1. Appendix C.3 explains the details. The resulting value is $\delta = 0.33$, which indicates a large downward shift in office demand in the WFH state. This shift is consistent with the evidence on the large decline in new leasing activity, documented in Figure 3.5.

The fixed costs and variable costs are assumed to be acyclical, making net operating income (revenue minus cost) more cyclical than revenues. Leasing commissions are also acyclical, and around 4.3% per year on leases that last an average of 7 years, for a total commission of 30% on a new lease. Leasing commissions on renewals of existing leases are set half as large as commissions on new leases. Leasing commissions are assumed to go down by 20% in the WFH state to reflect additional competition for brokerage business in a world where office demand is weak.

**Office Cash Flows for A+ Properties in NYC**

Next, we calibrate the model to A+ buildings of New York City. We use the leases on the subset of A+ buildings to get parameter estimates for the A+ NYC office sector. The calibration approach parallels that for All NYC, and is detailed in Appendix C.3. $\chi$ is set to be 0.14 to match the slightly higher average lease duration of 8.20 years of A+ leases in NYC. Table 3.4 lists the remaining parameter estimates for the A+ universe. The cost parameters are assumed to be the same as for the market as a whole.
Table 3.4: Calibration for NYC A+

<table>
<thead>
<tr>
<th>Variable</th>
<th>Symbol</th>
<th>E</th>
<th>R</th>
<th>WFH-E</th>
<th>WFH-R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market NER growth</td>
<td>$\epsilon$</td>
<td>0.0482</td>
<td>-0.1212</td>
<td>0.0272</td>
<td>-0.0472</td>
</tr>
<tr>
<td>Supply growth</td>
<td>$\eta$</td>
<td>-0.0155</td>
<td>-0.0081</td>
<td>-0.0410</td>
<td>-0.0336</td>
</tr>
<tr>
<td>Lease renewal share</td>
<td>$s^O$</td>
<td>0.8432</td>
<td>0.5668</td>
<td>0.5361</td>
<td>0.3604</td>
</tr>
<tr>
<td>New leasing share</td>
<td>$s^V$</td>
<td>0.1160</td>
<td>0.1893</td>
<td>0.0738</td>
<td>0.1204</td>
</tr>
</tbody>
</table>

3.3.4 Identifying the Persistence of Work From Home

A key parameter in the calibration is $p$, which governs the persistence of remote work. We identify this parameter as follows. We assume that the economy transitioned from the no-WFH expansion state (the E state) in 2019 to the WFH state and a recession (the WFH-R state) in 2020. We compute the model-implied return on the NYC A+ office market in this transition, using the A+ calibration described above:

$$\left(\frac{\tilde{V}^A+\left(\tilde{Q}_{20}^O, \tilde{R}_{20}^O, WFHR\right)}{\tilde{V}^A+\left(\tilde{Q}_{19}^O, \tilde{R}_{19}^O, E\right)} \frac{\left(\tilde{Q}_{20}^m\right)_{20}}{\left(\tilde{Q}_{19}^m\right)_{19}} + \frac{\tilde{NOI}^A+\left(\tilde{Q}_{20}^O, \tilde{R}_{20}^O, WFHR\right)}{\tilde{V}^A+\left(\tilde{Q}_{19}^O, \tilde{R}_{19}^O, E\right)}\right) = (1 - 22.75\%) \,.$$

Figure 3.11 plots this model-implied realized return on A+ office in this transition, the left-hand side of the equation above, for a range of values of $p$. Since the office return in this transition varies strongly with $p$, this moment is well-suited to identify this parameter.

In order to pick the relevant point on this curve, we turn to the REIT data. REITs invest in class A+ office properties. The three NYC-centric office REITs, (SL Green, Vornado, and Empire State Realty Trust), experienced a value-weighted return of -36.16% between December 2019 and December 2020. After unlevering this equity return, the asset return was -22.75%. The model matches this decline for a value of $p = 0.818$. With this key parameter identified, we can return to the calibration for the full NYC office market and calculate the change in its value due to remote

---

12 As the equation shows, this return depends also on the state pair $(\tilde{Q}_{20}^O, \tilde{R}_{20}^O)$ for 2019 and 2020, respectively. We obtain these by feeding in the sequence of annual aggregate shocks (expansions and recessions) from 1926 to 2019 obtained from the NBER recession chronology into the laws of motion of the states under the A+ calibration, which gives the 2019 values. For the 2020 values, we apply the law of motion for the state variables once more, assuming that the state transitioned from E to WFH-R.

13 Unlevering is done based on leverage ratio and cost of debt data from NAREIT.
3.4 Office Valuation Results

3.4.1 Key Model Outcomes

Table 3.5 presents the model solution for the “All NYC” office calibration. The model delivers a reasonable unconditional average cap rate of 7.74% for the overall NYC office market. The cap rate is 9.73% in recessions and 7.45% in expansions.\(^{15}\)

In a Gordon Growth Model with constant expected NOI growth rate \(g\) and a constant discount rate \(r\), the cap rate \(c = r - g\). Our Markov Chain model features time-varying expected growth and time-varying expected office returns, so this relationship does not hold. It is nevertheless useful to

---

\(^{14}\)We chose to calibrate to the full-year 2020 REIT return since the model is annual. Alternatively, one could use this calibration strategy to calibrate to the REIT return measured over at different periods. The observed office REIT returns were more negative when measured over a shorter period from February 2020–April 2020, and also when measured over the longer period from December 2019–May 2022. This makes our results conservative. One could also use our procedure to update the implied persistence parameter over time.

\(^{15}\)The hedonic-adjusted cap rate for Manhattan Office averaged 5.3% over the period 2001–19 (Real Capital Analytics data), and model predicts 5.0% average cap rate for the same period. Cap rates were higher before 2001. Longer, national data from CBRE put the average office cap rate at 8%. Since our model’s steady state pertains to a longer period than 2001–19, the higher average is a good feature. Also, our data pertains to more than Manhattan. Cap rates are higher in the other boroughs than in Manhattan. RCA has no office cap rates for the outer boroughs. Finally, our cap rate pertains to the entire office stock and removes depreciation, which lowers the growth rate and increases the cap rate by 2.7% points. The model-implied cap rate on a building where cash-flow growth is not reduced by depreciation is therefore 5.0% rather than 7.7%. The RCA data also indicate higher cap rates in recessions (6.0% in 2001, 2008, 2009) than in expansions (5.2% for 2002–2007 and 2010–2019).
look at the two components of the cap rate. The model implies an expected return on NYC office of 7.70% and an office risk premium of 6.21%. This is naturally lower than the equity risk premium of 8.06% since an unlevered office property is less risky than the aggregate stock market (which is a levered investment). The office risk premium is substantially higher in recessions (10.16%) than in expansions (5.19%).

Table 3.5: Model Solution for NYC All Calibration

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Uncond</th>
<th>E</th>
<th>R</th>
<th>WFHE</th>
<th>WFHR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_f$</td>
<td>0.0149</td>
<td>0.0084</td>
<td>0.0467</td>
<td>0.0084</td>
<td>0.0467</td>
</tr>
<tr>
<td>Equity $\mathbb{E}[\text{Ret}] - 1$</td>
<td>0.0955</td>
<td>0.0773</td>
<td>0.1846</td>
<td>0.0746</td>
<td>0.1815</td>
</tr>
<tr>
<td>Equity $\text{RP} = \mathbb{E}[\text{Ret}] - 1 - R_f$</td>
<td>0.0806</td>
<td>0.0690</td>
<td>0.1379</td>
<td>0.0662</td>
<td>0.1348</td>
</tr>
<tr>
<td>Cap rate</td>
<td>0.0774</td>
<td>0.0745</td>
<td>0.0973</td>
<td>0.0676</td>
<td>0.0999</td>
</tr>
<tr>
<td>Office $\mathbb{E}[\text{Ret}] - 1$</td>
<td>0.0770</td>
<td>0.0603</td>
<td>0.1484</td>
<td>0.0684</td>
<td>0.1455</td>
</tr>
<tr>
<td>Office $\text{RP} = \mathbb{E}[\text{Ret}] - 1 - R_f$</td>
<td>0.0621</td>
<td>0.0519</td>
<td>0.1016</td>
<td>0.0600</td>
<td>0.0987</td>
</tr>
<tr>
<td>$\mathbb{E}[g_t]$</td>
<td>-0.0007</td>
<td>-0.0186</td>
<td>0.1256</td>
<td>-0.0565</td>
<td>0.1102</td>
</tr>
<tr>
<td>Vacancy rate = $1 - \hat{\mathcal{Q}}^O$</td>
<td>0.1500</td>
<td>0.1053</td>
<td>0.1600</td>
<td>0.2768</td>
<td>0.2865</td>
</tr>
<tr>
<td>$\hat{\text{Rev}}$</td>
<td>0.7876</td>
<td>0.7995</td>
<td>0.9067</td>
<td>0.6479</td>
<td>0.8087</td>
</tr>
<tr>
<td>$\hat{\text{Cost}}$</td>
<td>0.4138</td>
<td>0.4259</td>
<td>0.4141</td>
<td>0.3777</td>
<td>0.3755</td>
</tr>
<tr>
<td>$\hat{\text{NOI}} = \hat{\text{Rev}} - \hat{\text{Cost}}$</td>
<td>0.3738</td>
<td>0.3735</td>
<td>0.4926</td>
<td>0.2702</td>
<td>0.4331</td>
</tr>
<tr>
<td>$\hat{\mathcal{V}}^R$</td>
<td>8.4713</td>
<td>8.9948</td>
<td>8.1383</td>
<td>7.1768</td>
<td>6.7976</td>
</tr>
<tr>
<td>$\hat{\mathcal{V}}^C$</td>
<td>3.7269</td>
<td>4.0427</td>
<td>3.1483</td>
<td>3.2731</td>
<td>2.5389</td>
</tr>
<tr>
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<td>4.9901</td>
<td>3.9037</td>
<td>4.2407</td>
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Expected NOI growth is close to zero (-0.07% per year) unconditionally. This number is in real terms and already incorporates that the office stock depreciates at 2.70% per year (so it is 2.63% before depreciation). Expected cash flow growth is higher in recessions than in expansions since recession states imply a high likelihood of transitioning to a better economic state going forward. The opposite is true of realized NOI growth rates in a transition from expansions to recessions, which are negative in the model (not reported).

The next part of the table shows that vacancy rates are 15% on average, higher in recessions than expansions by 5.47% points, and much higher conditional on being (and remaining) in the remote work states, around 27.9%.

The last part of the table shows the value of the building, scaled by potential rent, and broken
down into the PDV of revenues minus PDV of costs. The typical NYC office trades for a multiple of 4.74 times potential gross rent unconditionally according to our calibration. The average valuation ratio of office properties in the no-WFH expansion state of 4.95 is 16.78% higher than the value of 4.24 in the WFH-R state. Appendix Figure C.4 shows the valuation ratio for office \( \hat{V} \) conditional on expansion, recession, WFH-expansion and WFH-recession for NYC.

### 3.4.2 The Effect of WFH on Office Values

**Entire Office Stock**

To assess the effect of remote work on office values, we let the economy undergo the same transition as the one we considered for A+ office when calibrating the parameter \( p \), namely from an expansion in the no-WFH state in 2019 to a WFH-R state in 2020. We feed in the observed history of expansions and recessions from 1926-2019 to arrive at the value for the endogenous state variables \((\hat{Q}_t^O, \hat{R}_t^O)\) using the laws of motion for the states (3.2) and (3.3) under the “All NYC” calibration. The model captures the decade-long expansion before the Covid-19 pandemic. We then apply the law of motion once more to obtain \((\hat{Q}_t^O, \hat{R}_t^O)\) assuming the economy transitioned from E to WFH-R between 2019 and 2020.

The realized growth rate of potential gross rent in this transition is -20.42% in the model. The change in the scaled valuation ratio is -30.63%. Therefore, the overall value of the NYC office stock in this transition falls by 44.80%:

\[
\left( \frac{\hat{V}(\hat{Q}_{20}^O, \hat{R}_{20}^O, WFHR)}{\hat{V}(\hat{Q}_{19}^O, \hat{R}_{19}^O, E)} \right) \left( \frac{\hat{Q}_{20}^O R_{20}^m}{\hat{Q}_{19}^O R_{19}^m} \right) = (1 - 30.63\%) \cdot (1 - 20.42\%) = (1 - 44.80\%)
\]

Put differently, if the entire office stock of NYC had been publicly listed, its value would have fallen by 44.80% in 2020. This same decline was 27.13% for the A+ office sector, illustrating the relative safety of A+ office.

To understand the longer-run consequences of remote work, we conduct the following simulation exercise. In the first period of the transition, from 2019 to 2020, the economy goes from the E
to the WFH-R state. In the second year, from 2020 to 2021, the economy transitions from WFH-R to WFH-E. After 2021 (from 2022 onward), we let the economy evolve stochastically according to its laws of motion governed by $\pi$. Since there are many possible paths for the evolution of the state, Figures 3.12 and 3.13 show fan charts where darker blue colors indicate more likely future paths for the economy. The solid line indicates the mean path. The red line plots the average path conditional on the economy remaining in the WFH state every year until 2029. The probability of this event occurring is 19.97% according to the model.

Figure 3.12: Key Moments Distributions, Normalized to 100 in Dec 2019

Notes: The graph shows the evolution of the valuation ratio $\hat{V}$ for a transition from expansion in 2019 to WFH-R in 2020 and WFH-E in 2021. From 2022 onward, the state evolves stochastically. The shaded areas show percentiles of the distribution of simulated paths, with the darkest color indicating the 40–60 percentile range, and the lightest color the 10–90 percentile range.

The top left panel of Figure 3.12 shows the occupancy rate dynamics from the model simulation. The model captures a substantial decline in occupancy from a high value of 95.08% in 2019.
to an average value of 80% in 2022. Hence the model essentially matches the observed occupancy rate, which was 78.5% in 2022.Q2. Since long-term leases continue to roll off and renew at low rates as long as the economy is in the WFH state, the decline in occupancy is protracted. Should the economy remain in the WFH state until 2029, occupancy would eventually fall below 65% even after accounting for the supply response.\textsuperscript{16} Lease revenues, in the top right panel, reflect the protracted decline in occupancy and the gradual repricing of existing leases at lower market rents. The model predicts a decline in active lease revenues ($O^O R^O$) of 17.46% between 2019 and 2021, which is close to the observed decline in active lease revenues in the CompStak data for New York City of 16.06% between December 2019 and May 2022. Lease revenues go down 28.47% by 2029 along the average path. Total lease revenue falls by much more for the red line, reflecting additionally the faster reduction in the overall quantity of office floor space.

The bottom left panel shows that NOI falls by less than revenues since costs also decline in occupancy. The bottom right panel shows that office cap rates were below 5.76% in 2019 in the model, after a decade-long expansion that increased occupancy and rents. Cap rates then increase in 2020, fall back in 2021 as the economy shifts from recession to expansion, and then gradually stabilize toward their unconditional mean of 7.74%.

The combination of declining cash flows and rising cap rates results in a substantial change in the value of office $V_t$, shown in Figure 3.13. The graph illustrates a mean path that sees no recovery. Remote work is a near-permanent shock. Ten years after the transition, office values remain at levels that are 39.18% below the valuation in 2019. Along some sample paths, the economy returns to the no-WFH state and sees increases in occupancy rates ($O^O$), rent revenues, and NOI. Along other sample paths, the economy remains in the WFH state (WFH-E or WFH-R) for a long period, and office valuations continue to fall. For example, conditioning on remaining in the WFH state for at least 10 years (red line), office valuation are 59.86% lower in 2029 than in 2019.

A second key message from the valuation exercise is that there is substantial uncertainty around

\textsuperscript{16}Recall that supply growth in the WFH state is 2.55% points lower per year in the WFH than in the no-WFH states. This captures reduced construction as well as conversion of office to alternative use.
the mean path. This uncertainty is driven both by the future state of the economy: the medium-frequency fluctuations between recession and expansion as well as by the lower-frequency uncertainty about the future evolution of remote work. Office valuations are subject to \textit{WFH risk}.

\textit{Flight To Quality}

The previous results referred to the entire NYC office stock. We now redo the simulations for the A+ segment, which has its own cash-flow parameters. We define the A+ as in Section 3.2.\textsuperscript{17} The results for cap rates, valuation ratios, and vacancy rates in the A+ office segment are reported in Appendix C.4. They show lower cap rates and lower expected returns in the A+ segment, consistent with the lower risk of this segment.

Figure 3.14 revisits the transition graph for office values. It shows substantially smaller value reductions both in the short- and in the long-run. The mean path has office values down by 20.67\% in 2029 compared to 2019. In the scenario where the economy remains in the WFH state until at least 2029, the decline in A+ office values is 35.28\%. The better performance is due to the stronger rent growth for A+ in the WFH states, and a lower risk premium for A+ office especially in the

\textsuperscript{17}Buildings which contain an expensive lease—defined as higher than the 90th percentile NER for the quarter and submarket—enter the A+ segment, and remain there for ten years.
WFH state. On the flip side, the performance of the complement of A+, A-/B/C-class office is strictly worse than the overall market. Its initial value decline is -68.78% compared to -44.80% for all office.

**Term Structure of Valuations**

We can decompose the (change in) office value into the contribution from each of the future cash flows. Appendix C.2.4 explains the procedure. Figure 3.15 plots the share of the total value of office that comes from each of the first 20 years of cash flows. The lines are downward sloping as cash flows in the near term are more valuable than cash flows farther in the future due to discounting. Each line refers to a different current state for the economy. Interestingly, in expansions (such as 2019) the contribution of the nearest-term cash flows is much smaller than in the WFH-R state (such as 2020). For the share of short-term in total cash flows to rise (in present-value) between 2019 and 2020, the value of the cash flows in the farther future must falls by more than in the near future. This occurs because rents (and NOI) in the short-term are largely locked in given the long-term nature of leases. Investors would be willing to pay a premium for buildings that have a lot of long-term pre-pandemic leases in place.

This pattern is unusual, compared to the equity markets, where Van Binsbergen, Brandt, and
Koijen (2012) find that the share of short-maturity equity cash flows falls in the mild recession of 2001, indicating an expected rebound in the near term, and stays flat in the deep recession of 2008, indicating a near-permanent shock to cash flows. Our results therefore suggest that the locked-in nature of commercial leases results in a different term structure of cash flow shocks in commercial real estate compared to other asset classes. In turn, this suggests that the shock to commercial office as a result of remote work may play out over an extended horizon.

**Robustness to Persistence of Remote Work**

To assess how sensitive our headline value reduction number is, we explore alternative values for the key parameter $p$. Figure 3.16 plots the difference in office values ($V$) between the model with no remote work in December 2019 and the model with remote work in December 2020. The vertical dashed line indicates our benchmark model with $p = 0.818$, which produces a 44.80% valuation decline in the transition. This same decline is around 30.31% for a value of $p$ that is half as large as our benchmark.
3.4.3 Other Office markets and Aggregate Impact

San Francisco and Austin

Appendix C.5 repeats the calibration exercise for San Francisco (SF) and Austin and reports the resulting valuation moments. Figure 3.17 below shows the main fan chart for the valuation of the stock of SF office (left panel) and Austin office (right panel). The short-run (long-run) declines in office values are 54.43% (42.94%) for SF and 23.19% (-1.12%) for Austin. The former are larger than for NYC, due to the more cyclical nature of the SF office sector and its larger WFH exposure. This is possibly driven by SF’s larger exposure to tenants from the technology sector who have embraced remote work. Austin’s valuation effects are smaller than NYC due to its milder office cycles and smaller exposure to the WFH shock. Adjusted for market coverage, the total office value destruction is $19.53 billion in SF ten years from now, while Austin does not have long-term value destruction.

Aggregate Impact

Table 3.6 compiles statistics on the top-20 U.S. office markets. It reports the quantity of active leases (in sf) in December 2019 (column (1)), the percent change in active lease revenue between December 2019 and May 2022 (column (2)), and the change in the quantity (column (3)) and
NER (column (4)) of newly-signed leases over the same period. These statistics are based on the CompStak data and show that the decline in leasing activity is widespread. NYC is not an outlier. The first two rows in the bottom panel compare the top-20 office markets to all 105 office markets in the data, and again show similar changes.

Column (5) calculates the change in office values over the first two years of the pandemic (from December 2019 to December 2021), expressed in December 2021 dollars. It combines the size of the market in column (1), the change in lease revenues reported in column (2), and the change in the value-to-revenue ratio from the model. For NYC, San Francisco, and Austin, we calibrated the model separately, delivering a valuation ratio change that is market-specific. The two-year value destruction is $47.5 billion for NYC, $14.6 billion for San Francisco, and $2.2 billion for Austin. For the other 17 large office markets, we use the market-specific size and leasing revenue change in columns (1) and (2) and combine them with the valuation ratio change for NYC to arrive at column (5). Summed across the top-20 markets, we obtain a $127.8 billion value loss. Extending the analysis to the remaining 85 office markets, we find an additional $51.7 billion in value destruction for a total of $179.6 billion across all 105 markets in the Compstak data.

CompStak does not provide universal coverage. Based on Cushman and Wakefield reports, we
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<th>State</th>
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<th>Active SF (mi)</th>
<th>Lease Rev Chg</th>
<th>New SF Chg</th>
<th>NER Chg</th>
<th>Value Chg</th>
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Notes: The table reports the quantity of active leases pre-pandemic (in million sf), the change in active leasing revenue (in % of pre-pandemic leasing revenue), the change in newly signed leases (% of pre-pandemic newly signed sf), the change in the net effective rent per sf on newly-signed leases (in % of pre-pandemic market NER), and the change in valuation (in 2021 December dollars) for top 20 markets and for all 105 markets in CompStak combined (last two rows). Pre-pandemic active space in column (1) is calculated in December 2019. The changes in columns (2)-(4) are measured between December 2019 and May 2022. The value change in column (5) measures the change in the total value of office in dollars between the end of 2019 and the end of 2021. It combines the change in the value-to-revenue ratio over the first two years of the pandemic from the model calibration with the size of the market in column (1) and the drop in leasing revenue in column (2). The value changes for New York, San Francisco, and Austin in the top panel are based on full calibrations of the model to each of these cities separately, while the change in the valuation-to-revenue ratio for the other 17 top-20 markets in the middle panel is based on the change in the valuation ratio from the New York City calibration. The aggregate numbers in columns (4) for the top-20 market and national NER changes are adjusted by submarket FEs to remove composition effects. Column (6) is the CompStak coverage ratio, measured as the ratio of pre-pandemic active leased space in CompStak and active leased space in Cushman & Wakefield data. Column (7) divides column (5) by the coverage ratio in column (6).

are able to obtain a December 2019 coverage ratio estimate for 18 of the top-20 markets, shown in column (6). A coverage ratio of 36.1% for the remaining 87 markets (=105-18) reconciles the total U.S. office inventory in CompStak to that in Cushman & Wakefield. To obtain our aggregate value impact statistic in column (7), we divide column (5) by column (6). We arrive at an aggregate $414.3 billion loss in office values nationwide over the 2019–2021 period. This number is close to the aggregate impact numbers reported in the introduction, which pertained to the short-run (2019–2020) and long-run (2019–2029) changes and used the same scaling-up procedure.
3.5 Discussion and Conclusion

The real estate sector provides a unique vantage point to study the large social shifts in the wake of the Covid-19 pandemic. We estimate a 44.80% decline in the value of New York City’s office stock at the outset of the pandemic. We estimate that remote work is likely to persist and result in long-run office valuations that are 39.18% below pre-pandemic levels. The numbers for NYC are not an outlier; we find similar effects across many of the largest office markets. Our novel commercial real estate valuation model is suitable for calibration to office markets in other locations and other commercial real estate sectors.

These valuation changes are large, but since about 80% of the office stock is privately-held and private transactions have been few and far between (and represent a heavily selected sample), it has been difficult to directly observe the valuation changes in the market place. One exception is office REIT stocks, whose (unlevered) valuations the model matches both in 2020 and in 2022. Other market indicators that have turned bearish are short interest (as a share of equity float) in office REIT stocks and the prices of CMBX tranches rated BBB−. Specifically, tranches in more recent CMBX vintages, which have a larger share of office collateral than earlier vintages, have experienced larger price declines (Figure 3.18).

Our results have important implications for future work practices. Firms and employees have invested considerably to advance remote work possibilities. This has enabled major changes in the locations where individuals work and live. Real estate markets provide important financial signals which can help assess how society perceives the net benefit of remote work.

Trends in office occupancy have prompted discussion on the merits of conversion of office, either from A-/B/C to A+ office or to alternative use such as multi-family. The former conversion could make sense in light of the flight to quality and the likely dearth of new office construction for years to come. The latter conversion makes sense in light of the lack of affordable housing in large cities, but often runs into issues relating to the structural feasibility, zoning restrictions, and return on investment. Older buildings tend to be more amenable to apartment conversion. Whether
Figure 3.18: Price of CMBX Insurance

Notes: The graph shows prices for the Markit CMBX index of credit default insurance for BBB- tranches in various CMBS deals. A price of 60 implies that a pool without early prepayments or defaults requires an upfront payment of roughly $40 per $100 original notional to initiate a trade purchasing protection against default, implying a 40%– expected loss. The different lines separate different vintages. CMBX series 6–9 were relatively heavy in retail exposure relative to office (i.e., series 7 has only 18% office exposure). By contrast CMBX series 10–13 have 31% office concentration on average.

and how these conversions take place will have an important impact on urban design. Given the negative externalities associated with office vacancy, there may be a role for local governments to subsidize the conversion.

Finally, the decline in office values and the surrounding CBD retail properties, whose lease revenues have been hit at least as hard as office, has important implications for local public finances. For example, the share of real estate taxes in NYC’s budget was 53% in 2020, 24% of which comes from office and retail property taxes.\(^{18}\) Given budget balance requirements, the fiscal hole left by declining CBD office and retail tax revenues would need to be plugged by raising tax rates or cutting government spending. Both would affect the attractiveness of the city as a place of residence and work. These dynamics risk activating a fiscal doom loop. With more people being able to separate the location of work and home, the migration elasticity to local tax rates and amenities may be larger than in the past. Future research should explore these implications and study the role for federal fiscal policy.

\(^{18}\) An additional 3% of tax revenue comes from a tax on real estate tenants.
References


Appendix A: Chapter 1: Desperate Capital Breeds Productivity Loss: Evidence from Public Pension Investments in Private Equity

A.1 Robustness of Aggregate Results

A.1.1 Uniform Treatment Effect Following 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.

\[ y_{i,t+j} = \alpha_j + \sum_c \theta_{c,j} D_{c,it} + \lambda_{0,j} L\text{FIRM}_i + \gamma_j P\text{E}_{it} + \epsilon_{i,t+j}, \quad j \in \{-5, \ldots, 5\} \]  

(A.1)

where \( y_{it} \) is the outcome variable in year over year growth rates from \( t+j-1 \) to \( t+j \) for firm \( i \), \( D_{c,it} \) is the set of 5,600 dummy variables representing cell \( c \) for firm \( i \) at time \( t \), \( L\text{FIRM}_i \) is the growth rate for firm \( i \) from \( t-3 \) to \( t-1 \), and \( P\text{E}_{it} \) is the dummy variable for a target firm. The coefficient of interest is the treatment effect \( \gamma_j \). 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.1 shows estimated coefficients for \( \gamma_j \) from specification (A.1) from years -5 to +5 relative to buyout. I find similar results to Figure 1.5.
Table A.1: Post Buyout Annual Growth Rates at Targets Relative to Controls, Deals 1997-2018 (Uniform Treatment Effect Approach)

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<th>Dependent Variable:</th>
<th>(1) Emp $g_{\text{Adj.} R^2}$</th>
<th>(2) Pay $g_{\text{Adj.} R^2}$</th>
<th>(3) Revenue $g_{\text{Adj.} R^2}$</th>
<th>(4) Pay $g$-Emp $g_{\text{Adj.} R^2}$</th>
<th>(5) Rev $g$-Emp $g_{\text{Adj.} R^2}$</th>
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<td>0.009 (0.018)</td>
<td>0.006 (0.016)</td>
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<td>0.026*** (0.013)</td>
<td>-0.010 (0.008)</td>
<td>0.021 (0.013)</td>
<td>16.1</td>
</tr>
<tr>
<td>Buyout Year -1</td>
<td>-0.013 (0.008)</td>
<td>-0.019** (0.009)</td>
<td>0.012 (0.013)</td>
<td>-0.006 (0.006)</td>
<td>0.025* (0.015)</td>
<td>17.7</td>
</tr>
<tr>
<td>Buyout Year</td>
<td>-0.017 (0.017)</td>
<td>-0.012 (0.021)</td>
<td>-0.080*** (0.015)</td>
<td>0.005 (0.011)</td>
<td>-0.063*** (0.020)</td>
<td>18.3</td>
</tr>
<tr>
<td>Buyout Year +1</td>
<td>-0.067*** (0.024)</td>
<td>-0.061** (0.025)</td>
<td>-0.022 (0.015)</td>
<td>0.006 (0.013)</td>
<td>0.045* (0.027)</td>
<td>16.6</td>
</tr>
<tr>
<td>+2</td>
<td>-0.062** (0.029)</td>
<td>-0.038 (0.026)</td>
<td>-0.032 (0.025)</td>
<td>0.023 (0.016)</td>
<td>0.030 (0.036)</td>
<td>13.8</td>
</tr>
<tr>
<td>+3</td>
<td>-0.024 (0.017)</td>
<td>-0.045* (0.027)</td>
<td>-0.045** (0.019)</td>
<td>-0.020 (0.017)</td>
<td>-0.021 (0.019)</td>
<td>11.5</td>
</tr>
<tr>
<td>+4</td>
<td>0.027 (0.018)</td>
<td>0.043** (0.021)</td>
<td>-0.011 (0.022)</td>
<td>0.016 (0.012)</td>
<td>-0.038* (0.021)</td>
<td>9.6</td>
</tr>
<tr>
<td>+5</td>
<td>-0.007 (0.015)</td>
<td>-0.019 (0.016)</td>
<td>-0.0004 (0.016)</td>
<td>-0.012 (0.011)</td>
<td>0.007 (0.022)</td>
<td>8.2</td>
</tr>
<tr>
<td>Cell FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Lagged Firm g</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The table displays coefficients $\gamma_j$ in the regression specification (A.1):

$$y_{i,t+j} = \alpha_j + \sum_c \theta_{c,j} D_{cit} + \lambda_0_i L\text{FIRM}_i + \gamma_j P\text{E}_{it} + \epsilon_{i,t+j}, \quad j \in \{-5, \ldots, 5\}$$

$D_{cit}$ 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.1.2 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. Figure A.1 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 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.1: U.S. PE Target and Controls, PE Deals: 2000-2015

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 $t_0$. 

1The 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.2 shows the dynamic and static difference in difference coefficients. The results are similar to Figure 1.5 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.2: Difference in Differences for U.S. PE Targets Vs. Controls, PE Deals: 2000-2015

(A) Employment \( g \)

(B) Revenue \( g \)

(C) Rev \( g \) - Emp \( g \)

(D) Cumulative Changes

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Emp ( g )</th>
<th>Rev ( g )</th>
<th>Rev ( g ) - Emp ( g )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment × Post Buyout</td>
<td>(-0.0194^{**})</td>
<td>(-0.0212^{***})</td>
<td>(-0.0018)</td>
</tr>
<tr>
<td>Industry × Age × Size × Type × Transaction Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Lagged Firm ( g )</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Weighted Emp ( I_0 )</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>18,060,000</td>
<td>18,060,000</td>
<td>18,060,000</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td>0.0340</td>
<td>0.0392</td>
<td>0.0081</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0091</td>
<td>0.0152</td>
<td>0.0061</td>
</tr>
</tbody>
</table>

(E) Long Run Effects

Notes: Panels A-C show coefficients \( \gamma_j \) of the difference in difference specification:

\[
y_{it} = \alpha_t + \sum_{j=-5}^{5} \gamma_j (\text{PE}_i \times \text{Buyout Year}_{it+j}) + \sum_c \theta_c D_{c, it} + \lambda_0 LFIRM_i + \epsilon_{it}
\]

\( D_{c, it} \) 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 \( \gamma \). Significance levels: \(* * * p < 0.01, ** p < 0.05, * p < 0.10\).
A.1.3 Employment Effects for a Longer Time Period

Figure A.3: Employment at Target and Control Firms Pre and Post Buyout, PE Deals 1979-2014

Notes: The figure shows 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 characteristics: industry, size, age, type of firm, and transaction year. Year 0 captures the effect of the buyout.

Figure A.4: Non Parametric: One Year Employment Growth Rate Relative to Buyout Year

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 characteristics: 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.5: Difference in Differences Estimated Coefficients $\gamma_j$ for Employment Growth Rates Over Time Relative to Buyout Year

Notes: Figures plot difference in difference coefficients $\gamma_j$ from equation (1.1) for employment growth rates. Panel A considers PE deals from 1979-2018, and Panel B considers deals in 1979-2014.

Table A.2: Number of Targets In Years Relative to Buyout, PE Deals 1979-2014

<table>
<thead>
<tr>
<th>Year Relative to Buyout:</th>
<th>Number of Targets</th>
</tr>
</thead>
<tbody>
<tr>
<td>-5</td>
<td>4,600</td>
</tr>
<tr>
<td>-4</td>
<td>4,800</td>
</tr>
<tr>
<td>-3</td>
<td>5,100</td>
</tr>
<tr>
<td>-2</td>
<td>5,300</td>
</tr>
<tr>
<td>-1</td>
<td>5,400</td>
</tr>
<tr>
<td>0</td>
<td>5,400</td>
</tr>
<tr>
<td>1</td>
<td>4,900</td>
</tr>
<tr>
<td>2</td>
<td>3,700</td>
</tr>
<tr>
<td>3</td>
<td>3,300</td>
</tr>
<tr>
<td>4</td>
<td>3,000</td>
</tr>
<tr>
<td>5</td>
<td>2,700</td>
</tr>
</tbody>
</table>

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.4 shows one year employment growth rates for target and control firms considering PE deals from 1979 to 2018 (Panel A) and 1979 to 2014 (Panel B). I find similar results for deals from 2001-2014.
Table A.3: Estimated Coefficients of Post Buyout Employment Growth Rate

Panel (A) 1979-2018

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post Buyout</td>
<td>-0.287***</td>
<td>-0.177***</td>
<td>-0.133***</td>
<td>-0.156***</td>
<td>-0.119***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.020)</td>
<td>(0.014)</td>
<td>(0.018)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Firm Size FE</td>
<td></td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm Age FE</td>
<td></td>
<td></td>
<td>Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry FE</td>
<td></td>
<td></td>
<td></td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Type of Unit FE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Firm g</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Weighted Emp t₀</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>154,000</td>
<td>140,000</td>
<td>140,000</td>
<td>140,000</td>
<td>140,000</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.0623</td>
<td>0.0684</td>
<td>0.2870</td>
<td>0.0810</td>
<td>0.2960</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0382</td>
<td>0.0356</td>
<td>0.0356</td>
<td>0.0356</td>
<td>0.0356</td>
</tr>
</tbody>
</table>

Panel (B) 1979-2014

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post Buyout</td>
<td>-0.277***</td>
<td>-0.177***</td>
<td>-0.135***</td>
<td>-0.156***</td>
<td>-0.119***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.022)</td>
<td>(0.016)</td>
<td>(0.022)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Firm Size FE</td>
<td></td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm Age FE</td>
<td></td>
<td></td>
<td>Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry FE</td>
<td></td>
<td></td>
<td></td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Type of Unit FE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Firm g</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Weighted Emp t₀</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>102,000</td>
<td>93,500</td>
<td>93,500</td>
<td>93,500</td>
<td>93,500</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.0615</td>
<td>0.0756</td>
<td>0.3270</td>
<td>0.0894</td>
<td>0.3370</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0298</td>
<td>0.0238</td>
<td>0.0238</td>
<td>0.0238</td>
<td>0.0238</td>
</tr>
</tbody>
</table>

Notes: The table displays coefficients $\alpha_0$ of the event study specification (1.3):

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

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

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Figure A.6: 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 (1.11) 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.1.4 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 microdata, 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.7 shows specification (1.11) with year fixed effects (Panel A), and year and industry fixed effects (Panel B). Standard errors are clustered at the firm level.

Figure A.7: Dynamic Estimates of Post Buyout Over Time Relative to Buyout Year, PE Deals 2008-2021 (Revelio Labs Data)

(A) Year Fixed Effects

(B) Year, Industry Fixed Effects

Notes: Figures show dynamic event study estimates of employment growth rates from specification (1.11) 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.1.5 Different Random Samples using Census Micro-Data

Table A.4: Estimated Coefficients for Difference in Difference, PE Deals 1997-2018 (Multiple Random Samples of Control Firms)

<table>
<thead>
<tr>
<th></th>
<th>Random Sample 2</th>
<th>Random Sample 3</th>
<th>Random Sample 4</th>
<th>Random Sample 5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable:</strong></td>
<td>Emp g (1)</td>
<td>Pay g (2)</td>
<td>Rev g (3)</td>
<td>Pay g-Emp g (4)</td>
</tr>
<tr>
<td>Treatment × Post Buyout</td>
<td>-0.0247*** (0.0099)</td>
<td>-0.0243*** (0.0105)</td>
<td>-0.0269*** (0.0081)</td>
<td>0.0004 (0.0029)</td>
</tr>
<tr>
<td>Observations</td>
<td>25,440,000</td>
<td>25,440,000</td>
<td>25,440,000</td>
<td>25,440,000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.0395</td>
<td>0.0561</td>
<td>0.0454</td>
<td>0.0101</td>
</tr>
<tr>
<td></td>
<td>Random Sample 3</td>
<td>Random Sample 4</td>
<td>Random Sample 5</td>
<td></td>
</tr>
<tr>
<td><strong>Dependent Variable:</strong></td>
<td>Emp g (1)</td>
<td>Pay g (2)</td>
<td>Rev g (3)</td>
<td>Pay g-Emp g (4)</td>
</tr>
<tr>
<td>Treatment × Post Buyout</td>
<td>-0.0266*** (0.0103)</td>
<td>-0.0241** (0.0106)</td>
<td>-0.0281*** (0.0078)</td>
<td>0.0025 (0.0026)</td>
</tr>
<tr>
<td>Observations</td>
<td>25,430,000</td>
<td>25,430,000</td>
<td>25,430,000</td>
<td>25,430,000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.0362</td>
<td>0.0524</td>
<td>0.0422</td>
<td>0.0094</td>
</tr>
<tr>
<td></td>
<td>Random Sample 4</td>
<td>Random Sample 5</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Dependent Variable:</strong></td>
<td>Emp g (1)</td>
<td>Pay g (2)</td>
<td>Rev g (3)</td>
<td>Pay g-Emp g (4)</td>
</tr>
<tr>
<td>Treatment × Post Buyout</td>
<td>-0.0223*** (0.0084)</td>
<td>-0.0211** (0.0089)</td>
<td>-0.0254*** (0.0077)</td>
<td>0.0013 (0.0030)</td>
</tr>
<tr>
<td>Observations</td>
<td>25,440,000</td>
<td>25,440,000</td>
<td>25,440,000</td>
<td>25,440,000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.0368</td>
<td>0.0541</td>
<td>0.0401</td>
<td>0.0096</td>
</tr>
<tr>
<td></td>
<td>Random Sample 5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Dependent Variable:</strong></td>
<td>Emp g (1)</td>
<td>Pay g (2)</td>
<td>Rev g (3)</td>
<td>Pay g-Emp g (4)</td>
</tr>
<tr>
<td>Treatment × Post Buyout</td>
<td>-0.0290*** (0.0086)</td>
<td>-0.0253*** (0.0091)</td>
<td>-0.0293*** (0.0069)</td>
<td>0.0037 (0.0029)</td>
</tr>
<tr>
<td>Observations</td>
<td>25,450,000</td>
<td>25,450,000</td>
<td>25,450,000</td>
<td>25,450,000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.0378</td>
<td>0.0529</td>
<td>0.0415</td>
<td>0.0078</td>
</tr>
</tbody>
</table>

**Notes:** The table displays coefficients $\gamma$ of the difference in difference specification:

$$y_{it} = \alpha_t + \gamma (PE_t \times \text{Post}_t) + \sum_c \theta_c D_{cit} + \lambda_0 \text{LFIRM}_i + \epsilon_{it}$$

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

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A.1.6 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 1.5 and Table 1.2, I also control for lagged one year revenue controls for revenue growth effects. Figure A.8 shows similar results for both versions of the difference in difference.

Figure A.8: Difference in Difference Estimated Coefficients $\gamma_j$ Over Time Relative to Buyout Year, PE Deals 1997-2018 (Additional Controls)

(A) Employment $g$

(B) Revenue $g$

(C) Rev $g$ - Emp $g$

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Emp $g$</th>
<th>Rev $g$</th>
<th>Rev $g$ - Emp $g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment $\times$ Post Buyout</td>
<td>$-0.0288^*$</td>
<td>$-0.0295^{***}$</td>
<td>$-0.0009$</td>
</tr>
<tr>
<td>Industry $\times$ Age $\times$ Size $\times$ Type $\times$ Transaction Year $\times$ Year</td>
<td>$Y$</td>
<td>$Y$</td>
<td>$Y$</td>
</tr>
<tr>
<td>Controls</td>
<td>$Y$</td>
<td>$Y$</td>
<td>$Y$</td>
</tr>
<tr>
<td>Weighted Emp $t_0$</td>
<td>$Y$</td>
<td>$Y$</td>
<td>$Y$</td>
</tr>
<tr>
<td>Observations</td>
<td>19,030,000</td>
<td>19,030,000</td>
<td>19,030,000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.0407</td>
<td>0.0556</td>
<td>0.0080</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0202</td>
<td>0.0251</td>
<td>0.0049</td>
</tr>
</tbody>
</table>

(D) Long Run Effects

Notes: Panels A-C show coefficients $\gamma_j$ of the difference in difference specification (1.1):

$$y_{it} = \alpha_t + \sum_{j=-5}^{j=5} \gamma_j \left(\text{PE}_t \times \text{Buyout Year}_{t_0+j}\right) + \sum_{c} \theta_c D_{c,it} + \lambda_0 L\text{FIRM}_i + \epsilon_{it}$$

$D_{c,it}$ 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 $\gamma$. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^*p < 0.10$. 

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A.2 Additional Analysis of Aggregate Results

A.2.1 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 A.9: Difference in Difference Estimated Coefficients $\gamma_j$ Over Time Relative to Buyout Year for Wages, PE Deals 1997-2018

(A) Real Pay $g$  
(B) Pay $g$ - Emp $g$

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Pay $g$</th>
<th>Pay $g$-Emp $g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment $\times$ Post Buyout</td>
<td>$-0.0263^{***}$</td>
<td>$0.0011$</td>
</tr>
<tr>
<td>Industry $\times$ Age $\times$ Size $\times$ Type $\times$ Transaction Year FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Lagged Firm $g$</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Weighted Emp $l_0$</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>25,430,000</td>
<td>25,430,000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.0528</td>
<td>0.0087</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.0139</td>
<td>0.0042</td>
</tr>
</tbody>
</table>

(C) Long Run Effects

Notes: Panels A and B show coefficients $\gamma_j$ of the difference in difference specification (1.1):

$$y_{it} = \alpha_t + \sum_{j=-5, j\neq -1}^{j=5} \gamma_j (PE_t \times \text{Buyout Year}_{t_{0+j}}) + \sum_c \theta_c D_{c_{it}} + \lambda_0 \text{L Firm}_{t} + \epsilon_{it}$$

$D_{c_{it}}$ 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 $\gamma$. Significance levels: $^{***} p < 0.01$, $^{**} p < 0.05$, $^{*} p < 0.10$. 

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Table A.5: Event Study Estimated Coefficients of Post Buyout for Wages, PE Deals 1997-2018

(A) Real Pay $g$

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Pay $g$</th>
<th>Pay $g -\text{Emp } g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post Buyout</td>
<td>-0.075***</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Firm Size FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Firm Age FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Industry FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Type of Unit FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Lagged Firm $g$</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Weighted Emp $t_0$</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>70,000</td>
<td>70,000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.193</td>
<td>0.016</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>0.028</td>
<td>0.005</td>
</tr>
</tbody>
</table>

(B) Pay $g - \text{Emp } g$

(C) Long Run Effects

Notes: The table shows coefficients $\alpha_0$ of the event study specification (1.3):

$$y_{it} = \alpha_i + \alpha_0 \text{Post Buyout}_i + \gamma L\text{FIRM}_i + \text{Fixed Effects} + \epsilon_{it}$$

$L\text{FIRM}_i$ is lagged firm growth rate between year -3 and -1 relative to buyout. Fixed Effects includes 12 firm size categories, 5 firm age categories, 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. 
A.2.2 Manufacturing Targets

Figure A.10: Difference in Difference Estimated Coefficients $\gamma_{ij}$ for Manufacturing Firms Over Time Relative to Buyout Year, PE Deals 1997-2018

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

(D) Long Run Effects

Notes: Panels A-C display coefficients $\gamma_{ij}$ of the difference in difference specification (1.1) for manufacturing firms. Panel D shows coefficient $\gamma$ 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 $i$. Standard errors are clustered at the firm level to account for potential heterogeneity. Dotted red lines represent 90% confidence intervals. Significance levels: $*** p < 0.01$, $** p < 0.05$, $* p < 0.10$. 

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Emp g</th>
<th>Pay g</th>
<th>Rev g</th>
<th>Rev g-Emp g</th>
<th>$\Delta \log(TFP)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment $\times$ Post Buyout</td>
<td>-0.0076</td>
<td>-0.0082</td>
<td>-0.0183</td>
<td>-0.0107</td>
<td>0.0038</td>
</tr>
<tr>
<td>(0.0080)</td>
<td>(0.0082)</td>
<td>(0.0119)</td>
<td>(0.0120)</td>
<td>(0.0055)</td>
<td></td>
</tr>
<tr>
<td>Industry $\times$ Age $\times$ Size $\times$ Type $\times$ Buyout Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Weighted Emp $t_0$</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>4,106,000</td>
<td>4,106,000</td>
<td>4,106,000</td>
<td>4,106,000</td>
<td>4,106,000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.0373</td>
<td>0.0523</td>
<td>0.0369</td>
<td>0.0158</td>
<td>0.0110</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>-0.0019</td>
<td>0.0059</td>
<td>0.0081</td>
<td>0.0100</td>
<td>0.0018</td>
</tr>
</tbody>
</table>
A.2.3 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 private equity.

Following Song et al. (2018), I construct wage dispersion measures at firm level. Within firm \( t \) 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 \( t \),

\[
\text{var}_{it}(y_{wit}|w_{it}) = \sum_w \left(y_{wit} - \bar{y}_{it}\right)^2
\]

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 A.6: Estimated Difference in Difference Coefficients \( \gamma \) for Within Firm Wage Dispersion Over Time Relative to Buyout Year, PE Deals 1979-2018

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Within Firm Variance</th>
<th>Inter Quartile Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment × Post Buyout</td>
<td>0.169**</td>
<td>0.099*</td>
</tr>
<tr>
<td>Industry × Age × Size × Type × Transaction Year FE</td>
<td>( Y )</td>
<td>( Y )</td>
</tr>
<tr>
<td>Firm FE</td>
<td>( Y )</td>
<td>( Y )</td>
</tr>
<tr>
<td>Year FE</td>
<td>( Y )</td>
<td>( Y )</td>
</tr>
<tr>
<td>Controls</td>
<td>( Y )</td>
<td>( Y )</td>
</tr>
<tr>
<td>Weighted Emp ( t_0 )</td>
<td>( Y )</td>
<td>( Y )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>Under Disclosure</th>
<th>Under Disclosure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.606</td>
<td>0.673</td>
</tr>
<tr>
<td>Dependent Variable Mean</td>
<td>2.084</td>
<td>1.727</td>
</tr>
</tbody>
</table>

Notes: The table displays coefficients \( \gamma \) of the difference in difference specification:

\[
y_{it} = \alpha_t + \gamma(\text{PE}_i \times \text{Post}_t) + \sum_c \theta_c D_{c_{it}} + \lambda_0 \text{FIRM}_i + \epsilon_{it}
\]

\( D_{c_{it}} \) 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 observations are under disclosure at the Census. Significance levels: **\( p < 0.01 \), *\( p < 0.05 \), *\( p < 0.10 \).
Figure A.11 Panels A and B show within firm variation and inter-quartile range of log 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.

Figure A.11: Estimated Difference in Difference Coefficients $\gamma_j$ 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 $\gamma_j$ of the difference in difference specification (1.1). 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^*p < 0.10$.

A.3 Additional Investor Heterogeneity Results


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, Kramarz, and Margolis (1999). I add LP and GP interactions with
Post Buyout\(_{it}\) in specification (1.3):

\[
y_{it} = \alpha_t + \alpha_0 Post \text{ Buyout}_{it} + \sum_j \beta_j \left( Post \text{ Buyout}_{it} \times GP_j \right) + \sum_k \beta_k \left( Post \text{ Buyout}_{it} \times LP_k \right) + \gamma L\text{FIRM}_i + \text{Fixed Effects} + \epsilon_{it} \tag{A.3}
\]

Figure A.12 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 A.12: Model Explanatory Power for Real Outcomes at Targets Under Different Specifications

Notes: “Baseline” refers to equation (1.3), “LP FE” considers only heterogeneity based on LP and omits the interaction term (Post Buyout\(_{it} \times GP_j\)) from equation (A.3), “GP FE” considers only heterogeneity based on GP and omits the interaction term (Post Buyout\(_{it} \times LP_k\)) from equation (A.3), and “LP & GP FE” is equation (A.3). PE deals are from 1997 to 2018.
A.3.2 Only Public Pension Supported Firms

Figure A.13: Estimates of Post Buyout × Underfunded Ratio, PE Deals 1997-2018

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 (1.5) 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.
Notes: The figure plots estimated coefficients for labor productivity growth rates of Post × Pension Underfunded Split in equation (1.5) 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.
A.3.3 Additional Splits

In specification (1.5), 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 A.15 shows that the most underfunded public pensions supporting significant decreases in labor productivity is not driven by choice of splits.

Figure A.15: Estimates of Post Buyout × Investor Type, PE Deals 1997-2018

Notes: The figure plots estimated coefficients from equation (1.5) 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 A.16: 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 (1.5) 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.
A.4 GP Quality Heterogeneity

A.4.1 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.

\[
\text{Assets}_{j,t} = \sum_{j \in J} \text{Assets}_{j,t}
\]  

(A.4)

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.

A.4.2 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 A.17 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 A.17: 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 (1.5). Buyout includes firms financed by only balanced buyout strategy funds. Growth+Others 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.
A.5 Data Description

This section describes in detail the datasets used in the paper.

**Prequin:** Prequin 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). Prequin sources its data mainly from FOIA requests and relationships with general partners/ funds. More information can be found on https://pro.prequin.com/. I use the Prequin portal instead of the Wharton Research Data Service (WRDS) to download the data, as the portal has more detailed information than the WRDS database.

Prequin 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, Prequin 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 Prequin 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 its 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 compre-
sive 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](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](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 entities 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](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\(^2\), 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

\(^2\)Except for the state of Minnesota, which I do not have access to.
Dakota, New Jersey, New Mexico, Nevada, New York, Ohio, Oklahoma, Pennsylvania, 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 identifiers in the LBD. This is of essential as the firm identifiers 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.


**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 contributions, asset allocations, investment returns and horizon. More information can be found here: [https://publicplansdata.org/public-plans-database/](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.

A.6 Sample Construction

A.6.1 Cleaning Preqin and Merging Across Preqin Datasets

*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.

*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 domiciles, 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.

*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.
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”. Second, I keep targets in the U.S..

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 the investor, fund portfolio, and deals and portfolio companies files to get the investor - PE fund (also referred to as “fund family”) - sub PE fund - firm (or “portfolio

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

A.6.2 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 heirarchical 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 A.6.1, 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. I consider a year before as the targets might undergo a name or entity change, or might dissolve some

\[4\] I redo the match using two years before the deal, it does not change the result.
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.5

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

5More information on the variable can be found here: https://www2.census.gov/ces/wp/2021/CES-WP-21-08.pdf.
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.

A.6.3 Merging Private Equity Buyouts with Revenue Enhanced LBD

I combine all the LBD revised establishment year files. Next, I merge the output of Section A.6.2 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 1.1 shows the matched and unmatched targets by year, and Figure 1.18 shows by industry and state. The stringent match methodology explains the conservative matches.

A.6.4 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.

A.6.5 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).
A.6.6 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.

A.7 Variable Construction

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

A.7.1 Production Function Variables

Establishment Level.

The neoclassical production function, where $Y_{eit}$ is the real gross output 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.

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

(A.5)

The production function (A.5) is the main equation to calculate total factor productivity (TFP). Following Baily, Hulten, and Campbell (1992), $\ln TFP_{eit}$ representing plant-level log of total factor
Productivity can be written as,

\[
\ln TFP_{eit} = \ln Y_{eit} - \alpha_K \ln K_{eit} - \alpha_L \ln L_{eit} - \alpha_M \ln M_{eit}
\]  

(A.6)

I define each of the inputs in equation (A.6) 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.

\[
Y_{eit} = \frac{TVS_{eit} + (TIE_{eit} - TIB_{eit}) + (WIE_{eit} - WIB_{eit})}{PISHIP_i}, \quad \text{if } Y_{eit} > 0
\]

\[
Y_{eit} = \frac{TVS_{eit}}{PISHIP_i}, \quad \text{otherwise}
\]  

(A.7)

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\(_i\), 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 up to 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.

\[
K_{eit} = K_{eit-1} \times (1 - \delta_{it}) + I_{eit}
\]

(A.8)
$K_{etit}$ represents capital stock in period $t$. $\delta_{etit}$ is the depreciation rate between $t-1$ and $t$, and $I_{etit}$ is investments between $t-1$ and $t$. In terms of implementation, I calculate the capital stock separately for machinery and structures until 1985.

$$KEQ_{etit} = KEQ_{etit-1} \cdot (1 - EQDPR_{etit}) + \frac{NM_{etit}}{PIINVE} \tag{A.9}$$

$$KST_{etit} = KST_{etit-1} \cdot (1 - STDPR_{etit}) + \frac{NB_{etit}}{PIINVS} \tag{A.10}$$

where, $KEQ_{etit}$ and $KST_{etit}$ represent machinery and structures respectively, $EQDPR_{etit}$ and $STDPR_{etit}$ are depreciation rates, $NM_{etit}$ and $NB_{etit}$ 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.

$$K_{etit} = K_{etit-1} \cdot (1 - EQDPR_{etit}) + \frac{TCE_{etit}}{PIINVE} \tag{A.11}$$

$TCE_{etit}$ 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.

$$KEQ_{etit}^{initial} = \frac{MAE_{etit} \cdot (NKCEQ_{etit}/GKHEQ_{etit})}{PIINVE} \tag{A.12}$$

$$KST_{etit}^{initial} = \frac{BAE_{etit} \cdot (NKCST_{etit}/GKHST_{etit})}{PIINVS} \tag{A.13}$$

$$K_{etit}^{initial} = \frac{TAE_{etit} \cdot (NKCEQ_{etit}/GKHEQ_{etit})}{PIINVE} \tag{A.14}$$

$MAE_{etit}$, $BAE_{etit}$, and $TAE_{etit}$ are the nominal book values for machinery, buildings, and total assets. $NKCEQ_{etit}$ and $NKCST_{etit}$ are the two-digit industry level nominal net capital stocks for equipment.
and structures respectively, while $\text{GKHEQ}_t$ and $\text{GKHST}_t$ are the gross capital stocks. Combining Equations (A.9)-(A.11) and (A.12)-(A.14), I can iterate 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, Grim, and Haltiwanger (2014).

$$TH_{eit} = \frac{PH_{eit} \times SW_{eit}}{WW_{eit}}, \quad \text{if } SW_{eit} > 0, \ WW_{eit} > 0$$

$$TH_{eit} = PH_{eit}, \quad \text{otherwise} \quad (A.15)$$

**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 $CF_{eit}$.

$$CM_{eit} = \underbrace{CP_{eit} + CR_{eit} + CW_{eit}}_{=NE_{eit}} + \underbrace{EE_{eit} + CF_{eit}}_{=E_{eit}} \quad (A.16)$$

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.

$$M_{eit} = \frac{CP_{eit} + CR_{eit} + CW_{eit}}{PIMAT_t} + \frac{EE_{eit} + CF_{eit}}{PIEN_t} \quad (A.17)$$
**Elasticities.** \( \alpha_K, \alpha_L, \text{ and } \alpha_M \) 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. \( \alpha_K \) is the share of expenditure on capital, \( \alpha_L \) is the share of expenditure on labor, and \( \alpha_M \) 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, Grim, and Haltiwanger (2014).

Post obtaining the above inputs, one can calculate plant-level TFP using equation (A.6) 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.

\[
TC_{eit} = L_{eit} + M_{eit}
\]  

(A.18)

\( M_{eit} \) 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 \( \pi_{eit} \) is total value of shipments post subtracting total costs \( TC_{eit} \), scaled by shipments.

\[
\pi_{eit} = \frac{TVS_{eit} - TC_{eit}}{TVS_{eit}}
\]  

(A.19)

**Firm Level.**

\[
\pi_{it} = \sum_e w_{eit} \pi_{eit}
\]  

(A.20)

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.

**A.7.2 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 $t$:

$$\text{var}_i(y_{wit}|w \in i) = \sum_w \left( y_{wit} - \bar{y}_{it} \right)^2$$  \hspace{1cm} (A.21)

$\text{var}_i(y_{wit}|w \in i)$ 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.

$$\text{IQR}_{it} = y_{wit}^{p_{75}} - y_{wit}^{p_{25}}$$  \hspace{1cm} (A.22)

where, $y_{wit}^{p_{75}}$ and $y_{wit}^{p_{25}}$ represents the 75th and 25th percentile of wages within a firm-year.
Appendix B: Chapter 2: Flattening the Curve: Pandemic-Induced
Revaluation of Urban Real Estate

B.1 Additional Results

Figure B.1: Bid-rent Functions for San Francisco and New York

(A) New York — Rent
(B) New York — Price
(C) San Francisco — Rent
(D) San Francisco — Price

Notes: This Figure shows the bid-rent function for the San Francisco-Oakland-Berkeley CA and New York-Newark-Jersey City NY-NJ-PA MSAs. Panels on the left show the relationship between distance from the city center (the log of 1 + the distance in kilometers from City Hall) and the log of rents measured at the ZIP code level. Panels on the right repeat the exercise for prices. Both plots show this relationship prior to the pandemic (Dec 2019, in green) as well as afterwards (Dec 2020, in red).
Figure B.2: Change in the Bid-rent function

Notes: The figure shows the change in the bid-rent functions for New York (left) and San Francisco (right). Each observation corresponds to the changes in either rents (Panel A) or prices (Panel B) between Dec 2019 and Dec 2020 within each city, plotted against the distance to the center of the city.
Figure B.3: Changes in Rents and Prices Against Pre-Pandemic Levels

Notes: The changes in rents (Panel A) and prices (Panel B) against pre-pandemic levels of rents and prices for New York (left) and San Francisco (right). Each observation corresponds to the changes in either rents (Panel A) or prices (Panel B) between Dec 2019 and Dec 2020 within each city, plotted against the Dec 2019 log level of rents or prices.
Figure B.4: Pandemic Induced Changes in Prices and Rents without Sample Restrictions

Bid-Rent Curve

(A) Rent  
(B) Price

Changes Against Distance

(C) Rent  
(D) Price

Changes Against Pre-Pandemic Levels

(E) Rent  
(F) Price

Notes: The top two panels show the bid-rent function for the top 30 MSAs: the relationship between distance from the city center (the log of 1 + the distance in kilometers from City Hall) and the log of rents (Panel A) and prices (Panel B). Lighter points indicate ZIP codes, while darker points indicate averages by 5% distance bins (binscatter). Subsequent figures show changes in rents (Panels C & E) and prices (Panels D & F) against distance and the pre-pandemic levels of rents and prices.
Figure B.5: Changes in Listing Prices and Market Inventory without Sample Restrictions

Notes: The figure shows the relationship between changes in listing prices, measured as either the median listing price (Panel A) or the median listing price per sq. ft. (Panel B) with respect to distance at the ZIP level. The next two panels show the changes in two measures of market inventory, active listings (Panel C) and median days on market (Panel D) against distance from the center of the city the top 30 MSAs in the US. Each observation represents the change in the market inventory or listing price measure from Dec 2019 to Dec 2020. Listing counts greater than or equal to 20 per zip-month are considered, and observations with 12 month changes of median listing price per sq. ft. greater than 1000% are omitted.
Figure B.6: Changes in Listing Prices and Market Inventory

Notes: The figure show the relationship between changes in listing prices, measured as either the median listing price (Panel A) or the median listing price per sq. ft. (Panel B) with respect to distance. Each observation is at the ZIP code level, and measures the change in the listing price variable from 2019–Dec 2020, plotted against distance from the center of city for the New York MSA (left) as well as San Francisco (right). Observations with 12 month changes of median listing price per sq. ft. greater than 1000% are omitted. Panel C represents the change in market inventory, measured by the active listing count on Realtor against distance from the center of the city for New York (left) and San Francisco (right). Each observation is a ZIP Code and represents the change in the market inventory measure from Dec 2019 to Dec 2020. Listing counts greater than or equal to 20 per zip-month are considered.
Figure B.7: Price Changes against Changes in Inventory without Sample Restrictions

(A) Price change against active listing changes  
(B) Price and median days on market changes

Notes: Changes in prices against changes in two measures of inventories for the top 30 MSAs. Panel A plots the relationship between the percentage change in house prices from Dec 2019–Dec 2020 against the percentage change in active listings over this period. Panel B plots the same change in house prices against the percentage change in days on market over the same period. Listing counts greater than or equal to 20 per zip-month are considered.

Figure B.8: Population Change by Distance From Center: Nighttime Definition

(A) Baseline (5pm–8am)  
(B) 10pm–8am  
(C) 4am–8am

Notes: The figure plots the population change gradient from VenPath across different definitions of population measurement. All measures requires three or more pings nighttime pings in a given census tract to designate a user as a possible resident and require at least five associations of individuals with nighttime pings in the same location in the same month to assign a residence. All measures also measure population change from March 2020 – April 2020. Our baseline estimate measures nighttime as 5pm–8am (Panel A), but results are robust to the alternative nighttime definitions of 10pm–8am (Panel B) and 4am–8am (Panel C).
Figure B.9: Associations of Intracity Migration without Sample Restrictions

(A) Migration Against Distance

(B) Migration Against Work From Home

(C) Migration Against Rent

(D) Migration Against Price

Notes: This graph shows the change in population from February to March as measured in VenPath against log(1 + distance) to the city center (Panel A) and the Dingel and Neiman (2020) Work From Home metric at the ZIP level for the top 30 MSAs (Panel B). We also show the change in population plotted against changes in rents at the ZIP level (Panel D) and changes in prices (Panel D).
Figure B.10: Migration Against Distance, Rents, and Prices

Notes: The figure shows change in population measured in VenPath over the period March 2020 – April 2020 plotted against distance (Panel A), change in rents (Panel B) and changes in prices (Panel C) for New York City (left) and San Francisco (right).
Figure B.11: Net Migration Rates Using VenPath Data

Notes: The figure plots the net migration rate from VenPath across three MSAs: New York, San Francisco, Boston, as well as broad sample of all MSAs considered in Table 2.3. To measure net migration, we examine individual’s home tracts in February based on their preponderant nighttime ping activity. We then examine their home tract at the end of March, and estimate net migrants as the change in people who have out-migrated, compared with the number of have migrated into the ZIP code. Individuals who drop out of the data are not considered.
Figure B.12: Determinants of Rent and Price Gradient Changes by MSA

Notes: The figure plots the total effect of work from home, stringency measure (orthogonalized), and supply inelasticity measure (orthogonalized) on the rent (price) gradient in Panel A (Panel B). The total effect is calculated using $\beta_i - x_{ij}$ for covariate $i$ and MSA $j$, where $\beta_i$ is from column (5) of Panel A of Table 2.1 for rents, and Panel B of this table for prices. $x_{ij}$ corresponds to the covariates from this table measuring work from home, stringency, and the supply inelasticity index.
Figure B.13: Migration Rates Pre- and Post-Pandemic

Notes: The figure plots long-term trends in population growth before and after the pandemic period. We measure pre-pandemic population growth rates using ZIP code-level population from the American Community Survey 5-year data set in 2019 (covering the years 2015-2019) and in 2014 (covering the years 2010-2014), and compute the growth rate between the 2014 and 2019 population data. We then plot this growth rate as a function of the distance to the city center.
Figure B.14: Cumulative Rent Growth under Transitory Case for Top 30 MSAs, New York, San Francisco, Los Angeles

Notes: The figure shows the cumulative rent growth over all future years under the transitory case is predicted under two assumptions of the model: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$ at the ZIP level. These are plotted against log of $1 +$ distance from the MSA center. The cumulative rent changes are calculated using equation (2.6), but at the ZIP level.
### Table B.1: Top-30 MSAs

<table>
<thead>
<tr>
<th>#</th>
<th>MSA</th>
<th>Population (Millions)</th>
<th>Pre-pandemic Rent Gradient</th>
<th>Change in Rent Gradient</th>
<th>Pre-pandemic Price Gradient</th>
<th>Change in Price Gradient</th>
<th>Pre-pandemic Price Gradient*</th>
<th>Change in Price Gradient*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>New York-Newark-Jersey City, NY-NJ-PA</td>
<td>19.22</td>
<td>-0.095</td>
<td>0.069</td>
<td>-0.240</td>
<td>0.042</td>
<td>-0.220</td>
<td>0.029</td>
</tr>
<tr>
<td>2</td>
<td>Los Angeles-Long Beach-Anaheim, CA</td>
<td>13.21</td>
<td>-0.066</td>
<td>0.025</td>
<td>-0.215</td>
<td>0.003</td>
<td>-0.165</td>
<td>-0.002</td>
</tr>
<tr>
<td>3</td>
<td>Chicago-Naperville-Elgin, IL-IN-WI</td>
<td>9.46</td>
<td>-0.081</td>
<td>0.039</td>
<td>-0.311</td>
<td>0.004</td>
<td>-0.287</td>
<td>0.003</td>
</tr>
<tr>
<td>4</td>
<td>Dallas-Fort Worth-Arlington, TX</td>
<td>7.57</td>
<td>-0.021</td>
<td>0.023</td>
<td>-0.032</td>
<td>0.002</td>
<td>-0.074</td>
<td>-0.001</td>
</tr>
<tr>
<td>5</td>
<td>Houston-The Woodlands-Sugar Land, TX</td>
<td>7.07</td>
<td>-0.118</td>
<td>0.028</td>
<td>-0.035</td>
<td>0.010</td>
<td>-0.044</td>
<td>-0.013</td>
</tr>
<tr>
<td>6</td>
<td>Washington-Arlington-Alexandria, DC-VA-MD-WV</td>
<td>6.28</td>
<td>-0.101</td>
<td>0.026</td>
<td>-0.207</td>
<td>0.009</td>
<td>-0.179</td>
<td>0.005</td>
</tr>
<tr>
<td>7</td>
<td>Miami-Fort Lauderdale-Pompano Beach, FL</td>
<td>6.17</td>
<td>-0.032</td>
<td>0.019</td>
<td>-0.128</td>
<td>0.014</td>
<td>-0.171</td>
<td>0.011</td>
</tr>
<tr>
<td>8</td>
<td>Philadelphia-Camden-Wilmington, PA-NJ-DE-MD</td>
<td>6.10</td>
<td>-0.031</td>
<td>0.014</td>
<td>-0.079</td>
<td>0.005</td>
<td>0.015</td>
<td>-0.010</td>
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<tr>
<td>9</td>
<td>Atlanta-Sandy Springs-Alpharetta, GA</td>
<td>6.02</td>
<td>-0.047</td>
<td>0.028</td>
<td>-0.078</td>
<td>0.018</td>
<td>-0.216</td>
<td>-0.004</td>
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<tr>
<td>10</td>
<td>Phoenix-Mesa-Chandler, AZ</td>
<td>4.95</td>
<td>0.077</td>
<td>0.020</td>
<td>-0.070</td>
<td>-0.019</td>
<td>-0.109</td>
<td>-0.024</td>
</tr>
<tr>
<td>11</td>
<td>Boston-Cambridge-Newton, MA-NH</td>
<td>4.87</td>
<td>-0.149</td>
<td>0.043</td>
<td>-0.166</td>
<td>0.027</td>
<td>-0.237</td>
<td>0.019</td>
</tr>
<tr>
<td>12</td>
<td>San Francisco-Oakland-Berkeley, CA</td>
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<td>-0.098</td>
<td>0.054</td>
<td>-0.230</td>
<td>0.045</td>
<td>-0.203</td>
<td>0.045</td>
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<tr>
<td>13</td>
<td>Riverside-San Bernardino-Ontario, CA</td>
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<td>-0.025</td>
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<td>-0.185</td>
<td>0.005</td>
<td>-0.223</td>
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<tr>
<td>14</td>
<td>Detroit-Warren-Dearborn, MI</td>
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<td>0.194</td>
<td>-0.059</td>
<td>0.356</td>
<td>-0.057</td>
<td>0.037</td>
<td>-0.018</td>
</tr>
<tr>
<td>15</td>
<td>Seattle-Tacoma-Bellevue, WA</td>
<td>3.98</td>
<td>-0.099</td>
<td>0.052</td>
<td>-0.194</td>
<td>0.029</td>
<td>-0.183</td>
<td>0.026</td>
</tr>
<tr>
<td>16</td>
<td>Minneapolis-St Paul-Bloomington, MN-WI</td>
<td>3.64</td>
<td>0.012</td>
<td>0.019</td>
<td>-0.035</td>
<td>0.007</td>
<td>-0.099</td>
<td>-0.004</td>
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<tr>
<td>17</td>
<td>San Diego-Chula Vista-Carlsbad, CA</td>
<td>3.34</td>
<td>0.047</td>
<td>0.007</td>
<td>-0.021</td>
<td>-0.011</td>
<td>-0.081</td>
<td>-0.014</td>
</tr>
<tr>
<td>18</td>
<td>Tampa-St Petersburg-Clearwater, FL</td>
<td>3.19</td>
<td>-0.073</td>
<td>0.014</td>
<td>-0.037</td>
<td>0.006</td>
<td>-0.045</td>
<td>0.006</td>
</tr>
<tr>
<td>19</td>
<td>Denver-Aurora-Lakewood, CO</td>
<td>2.97</td>
<td>-0.064</td>
<td>0.023</td>
<td>-0.007</td>
<td>0.013</td>
<td>-0.053</td>
<td>-0.003</td>
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<tr>
<td>20</td>
<td>St Louis, MO-IL</td>
<td>2.80</td>
<td>0.108</td>
<td>0.006</td>
<td>-0.094</td>
<td>0.005</td>
<td>-0.060</td>
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<tr>
<td>21</td>
<td>Baltimore-Columbia-Towson, MD</td>
<td>2.80</td>
<td>0.037</td>
<td>0.000</td>
<td>0.066</td>
<td>0.000</td>
<td>0.164</td>
<td>-0.001</td>
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<tr>
<td>22</td>
<td>Charlotte-Concord-Gastonia, NC-SC</td>
<td>2.64</td>
<td>-0.125</td>
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<td>23</td>
<td>Orlando-Kissimmee-Sanford, FL</td>
<td>2.61</td>
<td>0.034</td>
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<td>-0.006</td>
<td>-0.047</td>
<td>-0.002</td>
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<tr>
<td>24</td>
<td>San Antonio-New Braunfels, TX</td>
<td>2.55</td>
<td>0.034</td>
<td>-0.010</td>
<td>0.024</td>
<td>0.003</td>
<td>0.030</td>
<td>0.011</td>
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<tr>
<td>25</td>
<td>Portland-Vancouver-Hillsboro, OR-WA</td>
<td>2.49</td>
<td>0.040</td>
<td>0.030</td>
<td>-0.060</td>
<td>0.014</td>
<td>-0.107</td>
<td>0.005</td>
</tr>
<tr>
<td>26</td>
<td>Sacramento-Roseville-Folsom, CA</td>
<td>2.36</td>
<td>0.054</td>
<td>0.022</td>
<td>0.066</td>
<td>0.002</td>
<td>-0.012</td>
<td>-0.005</td>
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<tr>
<td>27</td>
<td>Pittsburgh, PA</td>
<td>2.32</td>
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<td>0.434</td>
<td>0.002</td>
<td>-0.129</td>
<td>-0.033</td>
</tr>
<tr>
<td>28</td>
<td>Las Vegas-Henderson-Paradise, NV</td>
<td>2.27</td>
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<td>0.009</td>
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<tr>
<td>29</td>
<td>Austin-Round Rock-Georgetown, TX</td>
<td>2.23</td>
<td>-0.115</td>
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<td>-0.129</td>
<td>-0.009</td>
<td>-0.227</td>
<td>-0.024</td>
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<tr>
<td>30</td>
<td>Cincinnati, OH-KY-IN</td>
<td>2.22</td>
<td>-0.021</td>
<td>0.003</td>
<td>0.056</td>
<td>-0.019</td>
<td>0.004</td>
<td>0.031</td>
</tr>
</tbody>
</table>

*Notes: *: Gradients and changes in gradient calculated without restricting the sample to ZIP codes where both rent and price metrics are available.
Table B.2: Explaining the Cross-MSA Variation in Price Gradient Changes

<table>
<thead>
<tr>
<th></th>
<th>(1) Benchmark</th>
<th>(2) All ZIPs</th>
<th>(3) Pop&gt;5000</th>
<th>(4) Pop Weight</th>
<th>(5) Bed1</th>
<th>(6) Bed2</th>
<th>(7) Condo</th>
<th>(8) SFR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Work from Home</td>
<td>0.215***</td>
<td>0.128**</td>
<td>0.158**</td>
<td>0.166**</td>
<td>0.227***</td>
<td>0.171**</td>
<td>0.0816</td>
<td>0.227**</td>
</tr>
<tr>
<td>(0.0767)</td>
<td>(0.0704)</td>
<td>(0.0661)</td>
<td>(0.0679)</td>
<td>(0.0774)</td>
<td>(0.0649)</td>
<td>(0.0862)</td>
<td>(0.0862)</td>
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<tr>
<td>Orthogonalized Stringency Index</td>
<td>0.0838</td>
<td>0.110*</td>
<td>0.104*</td>
<td>0.128**</td>
<td>-0.0116</td>
<td>0.0234</td>
<td>-0.0367</td>
<td>0.0925</td>
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<tr>
<td>(0.0593)</td>
<td>(0.0545)</td>
<td>(0.0511)</td>
<td>(0.0525)</td>
<td>(0.0599)</td>
<td>(0.0502)</td>
<td>(0.0652)</td>
<td>(0.0652)</td>
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<tr>
<td>Orthogonalized Supply Inelasticity</td>
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<td>0.0177</td>
<td>0.0139</td>
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<td>0.000996</td>
<td>0.0108</td>
<td>0.0115</td>
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<tr>
<td>(0.0128)</td>
<td>(0.0117)</td>
<td>(0.0110)</td>
<td>(0.0113)</td>
<td>(0.0129)</td>
<td>(0.0108)</td>
<td>(0.0140)</td>
<td>(0.0140)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.0806**</td>
<td>-0.0521*</td>
<td>-0.0628**</td>
<td>-0.0675**</td>
<td>-0.0770**</td>
<td>-0.0610**</td>
<td>-0.0194</td>
<td>-0.0876**</td>
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<tr>
<td>(0.0303)</td>
<td>(0.0279)</td>
<td>(0.0262)</td>
<td>(0.0268)</td>
<td>(0.0306)</td>
<td>(0.0257)</td>
<td>(0.0340)</td>
<td>(0.0339)</td>
<td></td>
</tr>
</tbody>
</table>

Observations: 30 30 30 30 30 30 29 29

Adjusted $R^2$: 0.226 0.185 0.246 0.265 0.174 0.126 -0.035 0.199

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

Table B.3: Explaining the Cross-ZIP Variation in Price Changes

<table>
<thead>
<tr>
<th></th>
<th>(1) Benchmark</th>
<th>(2) All ZIPs</th>
<th>(3) Pop&gt;5000</th>
<th>(4) Pop Weight</th>
<th>(5) Bed1</th>
<th>(6) Bed2</th>
<th>(7) Condo</th>
<th>(8) SFR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Distance)</td>
<td>0.00669**</td>
<td>0.00329</td>
<td>0.00295</td>
<td>0.00489</td>
<td>0.0118***</td>
<td>0.00785***</td>
<td>0.00896***</td>
<td>0.00614***</td>
</tr>
<tr>
<td>(2.40)</td>
<td>(0.72)</td>
<td>(0.66)</td>
<td>(1.02)</td>
<td>(4.21)</td>
<td>(3.17)</td>
<td>(3.32)</td>
<td>(2.19)</td>
<td></td>
</tr>
<tr>
<td>Work from Home</td>
<td>-0.108***</td>
<td>-0.0758***</td>
<td>-0.0846***</td>
<td>-0.1000***</td>
<td>-0.0774***</td>
<td>-0.0986***</td>
<td>-0.0745***</td>
<td>-0.0886***</td>
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<tr>
<td>(-3.79)</td>
<td>(-3.58)</td>
<td>(-3.83)</td>
<td>(-4.57)</td>
<td>(-4.05)</td>
<td>(-5.44)</td>
<td>(-3.92)</td>
<td>(-4.38)</td>
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</tr>
<tr>
<td>Median Household Income ('000)</td>
<td>0.000115</td>
<td>0.000196***</td>
<td>0.000225***</td>
<td>0.000262***</td>
<td>0.0000425</td>
<td>0.0000755</td>
<td>0.0000179</td>
<td>0.0000468</td>
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<tr>
<td>(1.42)</td>
<td>(4.59)</td>
<td>(5.69)</td>
<td>(4.04)</td>
<td>(0.44)</td>
<td>(0.88)</td>
<td>(1.66)</td>
<td>(0.63)</td>
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</tr>
<tr>
<td>Median Age</td>
<td>0.000284</td>
<td>0.0000903</td>
<td>0.0000171</td>
<td>0.00002019</td>
<td>0.000109</td>
<td>0.000215</td>
<td>0.000166</td>
<td>0.0000436*</td>
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<td>(1.23)</td>
<td>(0.86)</td>
<td>(1.10)</td>
<td>(0.01)</td>
<td>(0.39)</td>
<td>(0.80)</td>
<td>(0.61)</td>
<td>(1.96)</td>
<td></td>
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<tr>
<td>Percent of Black Households</td>
<td>0.0283***</td>
<td>0.0369***</td>
<td>0.0333***</td>
<td>0.0365***</td>
<td>0.0160</td>
<td>0.0327***</td>
<td>0.0151</td>
<td>0.0316***</td>
</tr>
<tr>
<td>(2.91)</td>
<td>(6.60)</td>
<td>(6.43)</td>
<td>(6.49)</td>
<td>(1.62)</td>
<td>(3.23)</td>
<td>(1.52)</td>
<td>(3.55)</td>
<td></td>
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<tr>
<td>Share of High Income Households</td>
<td>-0.139**</td>
<td>-0.166***</td>
<td>-0.209***</td>
<td>-0.173***</td>
<td>-0.0756</td>
<td>-0.104</td>
<td>-0.191***</td>
<td>-0.129*</td>
</tr>
<tr>
<td>(-2.37)</td>
<td>(-3.81)</td>
<td>(-4.65)</td>
<td>(-3.46)</td>
<td>(-1.25)</td>
<td>(-1.60)</td>
<td>(-2.99)</td>
<td>(-2.68)</td>
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<tr>
<td>Log(Restaurants &amp; Bars)</td>
<td>-0.00327**</td>
<td>0.000171***</td>
<td>-0.000430</td>
<td>-0.00107</td>
<td>-0.00190</td>
<td>-0.00210</td>
<td>-0.00223</td>
<td>-0.00181*</td>
</tr>
<tr>
<td>(-2.15)</td>
<td>(2.89)</td>
<td>(-0.56)</td>
<td>(-0.92)</td>
<td>(-1.04)</td>
<td>(-1.27)</td>
<td>(-1.12)</td>
<td>(-1.71)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.108***</td>
<td>0.0829***</td>
<td>0.0954***</td>
<td>0.100***</td>
<td>0.0747***</td>
<td>0.0948***</td>
<td>0.0747***</td>
<td>0.0957***</td>
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<tr>
<td>(6.75)</td>
<td>(5.11)</td>
<td>(6.40)</td>
<td>(7.80)</td>
<td>(3.37)</td>
<td>(6.58)</td>
<td>(4.03)</td>
<td>(6.73)</td>
<td></td>
</tr>
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</table>

Notes: t statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
B.2 Data Appendix

B.2.1 ZORI Underlying Data and Construction

In this section, we describe the construction of the Zillow ZORI rental index which we use in this paper. The ZORI (and also ZHVI) indices are constructing using data from all platforms that are owned by the company Zillow, which includes Trulia, Hotpads, Naked Apartments, and StreetEasy, in addition to Zillow.com. Zillow also uses the Multiple Listing Services (MLS) data. It buys data from multi-family rental data aggregators, as well as from large multi-family landlords. As such, it has excellent coverage of both urban apartment complexes and suburban mom-and-pop single-family rentals who list directly on Zillow.

The ZORI index is a repeat-rent index. As a result, it only compares changes in rents within units over time. Just like repeat-sales indices, repeat-rent indices have the virtue that they control for well for housing unit characteristics including hard-to-measure aspects of quality. Just like repeat-sales indices, they have the downside that they result in fewer observations than hedonic indices since, by definition, it is harder to see two listings of the same rental unit than just one listing. This is the main reason why ZORI is not available for all ZIP codes.

To address representativeness, Zillow computes the fraction of housing units by decade of construction and by type, where type takes on three values (single-unit detached and attached, 2–4 units, and 5+ units), from the government’s American Community Survey (ACS), and reweights its (repeat) rental listings accordingly. The ACS data is taken from the latest five-year ACS. Because of this reweighting, ZORI is not affected by changes in the composition of listings over time. Concretely, the rental weight $w_i$ for a particular unit $i$ based on the decade of construction $d$ and structure type $u$ is:

$$w_i = \frac{S_i^{ACS}(d, u)}{S_i^{Zillow}(d, u)},$$

where $S_i^{ACS}(d, u)$ reflects the share of ACS units built in decade $d$, with structure type $u$ and $S_i^{Zillow}(d, u)$ is the share of Zillow listings with that same combination of unit characteristics.

As a consequence of (i) the massive amount of data it is based on, (ii) the re-weighting to
capture the distribution of the rental housing stock, and (iii) the within-rental change inherent to
the repeat-rent approach, the ZORI index should adequately capture the representative rental trends
we are interested in investigating.

B.2.2 Comparisons Across Different Rental Data Sets

Next, we investigate the representativeness of the Zillow rental data against other data sets. In Figure B.15 Panel A, we correlate the ZORI series with the HUD Fair Market Rent Index at the ZIP-code level. The Fair Market Rent index is the rent on a representative rental unit, which the government collects for the purposes of determining rental assistance amounts in the Section 8 Housing Voucher program. We combine FMR data for 1-, 2-, 3-, and 4-bedroom units, by aggregating them based on the frequency of each type of unit at the Census tract level. Both HUD FMR and ZORI data are for 2020. We find a high correlation of 79.8% at the ZIP code level.

Figure B.15 Panel B shows that the log difference between ZORI and HUD-FMR rents does not vary systematically by distance to the city center. The $R^2$ of a regression of the log difference in rents on $\log(1+\text{dist})$ is only 0.0059. This evidence suggests that rent levels in ZORI are broadly representative of rental markets in the U.S., and that potential data coverage issues are not biased in the dimension of distance from the city center.

Second, we also compare ZORI against Census ACS estimates in Figure B.15 Panel C. The ACS data are for the five-year ACS that ends in 2019; the ZORI data is for December 2019. Again, we find high comparability across these two data sets, with correlations in rent levels across zip codes of 80.6%. Figure B.15 Panel D shows little systematic difference in relative rents as a function of distance from the urban core of the MSA. The $R^2$ of this relationship is 0.0137.

Third, we compare against another private-sector rental data provider, Apartment List.\(^1\) Both Apartment List and ZORI data in this comparison are for December 2020. Figure B.15 Panel E also shows high comparability of ZORI and Apartment List rent data, with a correlation of 83.6% between rent levels in the cross-section of ZIPs. Figure B.15 Panel F shows minimal sensitivity of

\(^1\)Publicly accessible Apartment List data, with information on the methodology, can be found at https://www.apartmentlist.com/research/category/data-rent-estimates.
relative rents to distance from the city center. The $R^2$ of this relationship is 0.0525.

A final data set we explore to substantiate the representatives of ZORI data is the Bureau of Labor Statistic’s Consumer Price Index for all Urban Consumers: Rent of Primary Residence (hereafter, referred to as the “CPI Rental Index”). The CPI Rental Index is available for 20 MSAs, all of which are part of the top-30 MSAs in our sample. For two MSAs, the CPI Rental Index series in discontinued after 2017, so we end up having data for 18 out of the top 30 MSAs. Figure B.16 plots the difference in log CPI Rental Index between December 2014 and December 2020 against the same difference for ZORI (which starts in 2014). We see a strong positive correlation showing that the ZORI and the CPI Rental Index line up well in the cross-section of MSAs.

The overall conclusion of this analysis is that the Zillow ZORI index appears to line up with multiple alternative rental data sources, providing confidence that we are identifying representative patterns for the overall rental market in our analysis.
Figure B.15: Comparing Rental Series Across Data Sets

Notes: The figure plots Zillow data against other rental data series in levels and against distance to the city center. The top row uses rental data from the Department of Housing and Urban Development’s Fair Market Rents. Each observation is a ZIP code. The left panel compares rent levels for HUD FRM (x-axis) and ZORI (y-axis). The right panel plots log differences between ZORI and HUD FMR rent levels against \( \log(1 + dist) \), where distance is measured from the centroid of the metropolitan area. The centroid of the MSA is City Hall, except for New York where it is Grand Central Terminal. The second row uses rental data from the 2019 five-year American Community Survey and ZORI data for January 2019. The third row uses rental data from the Apartment List and ZORI for December 2020.
Figure B.16: Correlation Between CPI Rent of Primary Residence and ZORI at MSA level

Notes: The figure plots the relationship between the ZORI index at the ZIP level and the Bureau of Labor Statistic’s Consumer Price Index for all Urban Consumers: Rent of Primary Residence. We plot this index for 18 MSAs, excluding MSAs that do not have CPI data throughout our entire series. We plot the difference between the log CPI Rental Index between December 2014 and December 2020 against the same difference for ZORI over the same time period.

B.2.3 ZORI Coverage Across ZIPS

While Zillow ZHVI data is broadly available across U.S. ZIP codes, ZORI data is available in fewer ZIP codes. We investigate the representativeness of ZORI data across geographies, especially comparing areas by distance to the city center.

First, Figure B.17 Panel A shows that there is a strongly negative relationship between the share of renters in a ZIP code (from the ACS data) and distance from the city center. This means that rental index data coverage will naturally be declining as we get farther from the city center. Indeed, Figure B.17 Panel B shows that the frequency of reporting a ZORI index is declining as a function of distance from the city center.

Table B.4 analyzes the role of rental data availability and distance formally. It presents estimates of logit models where the dependent variable is the availability (1 or 0) of a ZORI index for a particular ZIP code. Column (1) of this table shows that ZORI rental data is indeed somewhat more likely to be absent for ZIP codes more distant from the city center. However, column (2) of
Figure B.17: Relationship between Distance and Rentership

(A) Rentership vs. Distance

(B) ZORI Coverage vs. Distance

Notes: Panel A of the figure shows the strong relationship between the fraction of individuals who rent, drawn from ACS data, against distance to the center of the city. Panel B shows, plotted together, the renter fraction against the probability that the ZIP code has ZORI data available.

Table B.4: ZORI Availability, Distance, and Rentership

<table>
<thead>
<tr>
<th></th>
<th>(1) ZORI Reported</th>
<th>(2) ZORI Reported</th>
<th>(3) ZORI Reported</th>
<th>(4) ZORI Reported</th>
<th>(5) ZORI Reported</th>
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<tr>
<td>ZORI Reported</td>
<td></td>
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<tr>
<td>Log Distance</td>
<td>-0.675***</td>
<td>-0.319***</td>
<td>-0.119***</td>
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<tr>
<td></td>
<td>(0.0293)</td>
<td>(0.0354)</td>
<td>(0.0450)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rentership</td>
<td>3.334***</td>
<td>2.554***</td>
<td>3.639***</td>
<td>3.420***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.124)</td>
<td>(0.150)</td>
<td>(0.214)</td>
<td>(0.230)</td>
<td></td>
</tr>
<tr>
<td>Median Income (1000)</td>
<td>0.0390***</td>
<td>0.0394***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00536)</td>
<td>(0.00538)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Share income &gt; $ 150k</td>
<td>3.700***</td>
<td>3.260***</td>
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<tr>
<td></td>
<td>(1.430)</td>
<td>(1.446)</td>
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<tr>
<td>Median Age</td>
<td>-0.000106</td>
<td>0.00258</td>
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<td></td>
<td>(0.00649)</td>
<td>(0.00659)</td>
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<tr>
<td>Share Black</td>
<td>0.712***</td>
<td>0.657***</td>
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<td></td>
<td>(0.169)</td>
<td>(0.170)</td>
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<tr>
<td>Population (1000)</td>
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<td>0.0719***</td>
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<tr>
<td></td>
<td>(0.00198)</td>
<td>(0.00199)</td>
<td></td>
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</tr>
<tr>
<td>Density (1000/km²)</td>
<td>-0.0609***</td>
<td>-0.0644***</td>
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<tr>
<td></td>
<td>(0.00979)</td>
<td>(0.00988)</td>
<td></td>
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</tr>
<tr>
<td>Constant</td>
<td>0.881***</td>
<td>-2.456***</td>
<td>-1.155***</td>
<td>-6.244***</td>
<td>-5.874***</td>
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<td></td>
<td>(0.0943)</td>
<td>(0.0539)</td>
<td>(0.152)</td>
<td>(0.363)</td>
<td>(0.390)</td>
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<tr>
<td>Observations</td>
<td>9657</td>
<td>9650</td>
<td>9650</td>
<td>9537</td>
<td>9537</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses.

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

This table estimates a logit model of the presence of the ZORI index in a ZIP code (1/0) using ZIP-code level characteristics. Column (1) shows a role for distance to city center to explain the availability of ZORI; column (2) includes only the rental rate drawn from ACS (Rentership). Column (3) includes both distance and rental rate measures, while columns (4) and (5) include other covariates drawn from ACS. Standard errors in parenthesis.* p < 0.10, ** p < 0.05, *** p < 0.01.
this table highlights the point that ZIP codes are missing rental data frequently because they simply lack renters (as measured by the ACS rentership rate). In fact, column (3) shows that including just the rentership rate drastically reduces the coefficient on distance from -0.675 in column (1) to -0.319 in column (3). This suggests that ZORI is substantially missing due to a lack of sufficient rental buildings. Including a larger set of demographic and income controls in column (5) further drives the coefficient on distance down to one-sixth of its initial estimate.

B.3 Present Value Model Analysis

B.3.1 Model Details

We briefly review the present-value model of Campbell and Shiller (1988), a standard tool in asset pricing.

Let $P_t$ be the price of a risky asset, in our case the house, $D_{t+1}$ its (stochastic) cash-flow, in our case the rent, and $R_{t+1}$ the cum-dividend return:

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t}.$$

We can log-linearize the definition of the cum-dividend return to obtain:

$$r_{t+1} = k + \Delta d_{t+1} + \rho p d_{t+1} - p d_t,$$

where all lowercase letters denote natural logarithms and $p d_t = p_t - d_t = -d p_t$. The constants $k$ and $\rho$ are functions of the long-term average log price-rent ratio. Specifically,

$$\rho = \frac{\exp(p d)}{1 + \exp(p d)}, \quad k = \log(1 + \exp(\overline{p d})) - \rho \overline{p d}. \quad (B.1)$$

By iterating forward on the return equation, adding an expectation operator on each side, and imposing a transversality condition (i.e., ruling out rational bubbles), we obtain the present-value
model of Campbell and Shiller (1988):

\[ pd_t = \frac{k}{1 - \rho} + E_t \left[ \sum_{j=1}^{+\infty} \rho^{j-1} \Delta d_{t+j} \right] - E_t \left[ \sum_{j=1}^{+\infty} \rho^{j-1} r_{t+j} \right]. \]  \hspace{1cm} (B.2)

A high price-rent ratio must reflect either the market’s expectation of higher future rent growth, or lower future returns on housing (i.e., future price declines), or a combination of the two.

This equation also holds unconditionally:

\[ \bar{p}d = \frac{k}{1 - \rho} + \frac{\bar{g}}{1 - \rho} - \frac{\bar{x}}{1 - \rho}, \]  \hspace{1cm} (B.3)

where \( \bar{g} = E[\Delta d_t] \) and \( \bar{x} = E[r_t] \) are the unconditional expected rent growth and expected return, respectively. Equation (B.3) can be rewritten to deliver the well-known Gordon Growth model (in logs) by plugging in for \( \bar{p}d \):

\[ \log \left( 1 + \exp \bar{p}d \right) - \bar{p}d = \bar{x} - \bar{g}. \]  \hspace{1cm} (B.4)

The left-hand side variable is approximately equal to the long-run rental yield \( \bar{D}/\bar{P} \).

Subtracting equation (B.3) from (B.2), we obtain:

\[ pd_t - \bar{p}d = E_t \left[ \sum_{j=1}^{+\infty} \rho^{j-1} (\Delta d_{t+j} - \bar{g}) \right] - E_t \left[ \sum_{j=1}^{+\infty} \rho^{j-1} (r_{t+j} - \bar{x}) \right]. \]  \hspace{1cm} (B.5)

Price-rent ratios exceed their long-run average, or equivalently rental yields are below their long-run average, when rent growth expectations are above their long-run average or expected returns are below the long-run expected return.

**Expected Rent Growth** In what follows, we assume that expected rent growth follows an autoregressive process. We denote expected rent growth by \( g_t \):

\[ g_t = E_t[\Delta d_{t+1}] \]
and assume an AR(1) for $g_t$:

$$g_t = (1 - \rho_g)\bar{g} + \rho_g g_{t-1} + \epsilon_t^g. \quad (B.6)$$

Under this assumption, the rent growth term in equation (B.5) can be written as a function of the current period’s expected rent growth in excess of the long-run mean:

$$E_t \left[ \sum_{j=1}^{+\infty} \rho^{j-1} (\Delta d_{t+j} - \bar{g}) \right] = \frac{1}{1 - \rho \rho_g} (g_t - \bar{g}). \quad (B.7)$$

**Expected Returns**  Similarly, we define expected returns by $x_t$

$$x_t \equiv E_t [r_{t+1}]$$

and assume an AR(1) for $x_t$ following Lettau and van Nieuwerburgh (2008), Binsbergen and Koijen (2010), Koijen and van Nieuwerburgh (2011):

$$x_t = (1 - \rho_x)\bar{x} + \rho_x x_{t-1} + \epsilon_t^x. \quad (B.8)$$

Under this assumption, the return term in equation (B.5) can be written as a function of the current period’s expected return in excess of the long-run mean:

$$E_t \left[ \sum_{j=1}^{+\infty} \rho^{j-1} (r_{t+j} - \bar{x}) \right] = \frac{1}{1 - \rho \rho_x} (x_t - \bar{x}). \quad (B.9)$$

**Implied Dividend Growth Expectations**  With equations (B.7) and (B.9) in hand, we can restate equation (B.5)

$$pd_t - \bar{d} = A(g_t - \bar{g}) - B(x_t - \bar{x}). \quad (B.10)$$

where $A = \frac{1}{1 - \rho \rho_g}$ and $B = \frac{1}{1 - \rho \rho_x}$.
From equation (B.10), we can back out the current-period expectations about future rent growth:

\[
g_t = \bar{g} + (1 - \rho \rho_g) \left( pd_t - \bar{pd} \right) + \frac{1 - \rho \rho_g}{1 - \rho \rho_x} (x_t - \bar{x}). \tag{B.11}
\]

Current beliefs about rent growth depend on long-run expected rent growth (first term), the deviation of the price-rent ratio from its long-run mean (second term), and the deviation of expected returns from their long-run mean (third term). Long-run expected dividend growth \(\bar{g}\) is obtained from equation (B.3) given \(\bar{p}d\) and \(\bar{x}\).

**B.3.2 Additional Results**

**Expected Rent Growth For Individual MSAs** Figure B.18 reports the combination model’s prediction for expected urban-minus-suburban rent growth, relative to the pre-pandemic level, for individual MSAs. The reported number is a cumulative discounted change over many years. The two sets of bars correspond to the two different assumptions on expected returns. There is substantial variation in predicted urban rent growth revival, with large values for Los Angeles, Sacramento, Charlotte, Philadelphia, and Phoenix.

**Implications for Dynamics of Price-Rent Ratios** Finally, we show the evolution of the (population-weighted average) urban-minus-suburban price-rent ratio (Figure B.19). The initial increase in the transitory case is the same in the left and in the right panel because it is dictated by the 2020.Q4 data. From that point forward, the dynamics in the price dividend ratio are governed by the dynamics of expected rent growth and expected returns. We see a gradual decline in urban relative to suburban price-rent ratios in the left panel as expected rent growth mean-reverts. In the right panel, expected returns also mean-revert (at a slower pace because \(\rho_x > \rho_g\)), which leads to richer dynamics that exhibit under-shooting after year four. In the permanent case, the price-rent ratio remains at its 2020.Q4 level permanently. For our preferred combination case, we obtain urban price-rent ratios that remain about 1% point above the pre-pandemic levels in the long-run. Owning in the city center becomes permanently more expensive than renting.
Figure B.18: Change in Urban Minus Suburban Rent Growth Relative to Pre-Pandemic for Combination of Transitory and Permanent Regime

Notes: The figure shows the change in urban minus suburban rent growth relative to the pre-pandemic level for the combined regime across our sample of Top 30 MSAs. The combined case is calculated using weights as $p = 0.64$ for the transitory regime, and $1 - p = 0.36$ for the permanent regime, as reported by the Pulsenomics survey. We consider two cases as in Table 2.3: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$.

Figure B.19: Evolution of Price-Rent Ratio when Pandemic is Transitory and Permanent along with a Combination of Two Regimes

Notes: The figure shows the evolution of urban minus suburban price-rent ratio pre- and post-pandemic in scenarios in which the pandemic is transitory, permanent, and combining both regimes. We plot the population weighted average of the MSAs. We consider two cases as in Table 2.3: (1) $\Delta x = 0$, and (2) $\Delta x = 0.01$. 

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Appendix C: Chapter 3: Work From Home and the Office Real Estate Apocalypse

C.1 Asset Pricing Model to Infer Expected Returns

We develop a simple model to help understand how expected returns (risk premia) on office properties were affected during the pandemic.

C.1.1 Model for Expected Returns

We propose the following model for the expected log return on office REITS $r^{o}_t$:

$$x_t \equiv \mathbb{E}_t[r^{o}_{t+1}] = r^f_t + \beta_t^m \lambda^m + \beta_t^b \lambda^b + \beta_t^{wfh} \lambda^{wfh}$$

Office REITs are exposed to three sources of risk: aggregate stock market risk, aggregate bond market risk, and the systematic risk associated with remote work. In addition, their expected returns reflect the evolution of short-term nominal bond yields $r^f_t$. To capture the changes in the underlying risk structure during the pandemic, we allow the exposures of office REITs to vary over time.

C.1.2 Constructing a WFH Equity Risk Factor

We form a portfolio (Working From Home Index) that goes long stocks which benefit from remote work, and short stocks which suffer from the move to working-from-home. This entails long positions in the technology sector, health care sector, and pharmaceutical companies developing vaccine candidates and short positions in the transportation sector, entertainment sector, and hotel sector. The WFH index composition can be found in Table C.1. Several variations on the
factor construction, such as excluding entertainment stocks or just going long technology stocks and short transportation stocks, give similar results.

The WFH risk factor is a monthly rebalanced, long-short market capitalization weighted basket of stocks. On the last working day \( r \) of each month, which we call the rebalance day, each stock \( i \) in the long leg is assigned a weight \( w_{i,l,r} \) and each stock \( j \) in the short leg is assigned a weight \( w_{j,s,r} \),

\[
    w_{i,l,r} = \frac{S_{i,r-1}}{\sum_{k \in c_{l,r}} S_{k,r-1}}; \quad w_{j,s,r} = \frac{S_{j,r-1}}{\sum_{k \in c_{s,r}} S_{k,r-1}}
\]

where \( S_{k,r-1} \) is the market capitalization of stock \( k \) on day \( r - 1 \), the working day immediately preceding rebalance day \( r \), and \( c_{l,r} \) and \( c_{s,r} \) are the constituents in long and short legs respectively for rebalance date \( r \). Further, we impose weight caps of 10% on each stock in the long leg and 20% on each stock in the short leg.

The remaining weights are redistributed among remaining stocks of that leg in the same proportion above, i.e. proportional to their market capitalization, such that:

\[
    \sum_{k \in c_{l,r}} w_{k,l,r} = 1; \quad \sum_{k \in c_{s,r}} w_{k,s,r} = 1
\]

Once weights are assigned, daily returns of the long and short leg are calculated as follows:

\[
    R_{l,t} = \sum_{k \in c_{l,t}} w_{k,l,t} \left( \frac{P_{k,t}}{P_{k,t-1}} - 1 \right)
\]

\[
    R_{s,t} = \sum_{k \in c_{s,t}} w_{k,s,t} \left( \frac{P_{k,t}}{P_{k,t-1}} - 1 \right)
\]

where \( R_{l,t} \) and \( R_{s,t} \) are the returns of the long and short legs of the Index and \( P_{k,t} \) is the price of stock \( i \) on day \( t \). \( w_{k,x,t} \) is the weight of stock \( k \) in leg \( x \) on date \( t \), if \( t \) is a rebalance date and the weight of stock \( k \) in leg \( x \) on the rebalance date immediately preceding date \( t \) otherwise.
The daily return \( R_t \) on the working from Index on date \( t \) is then given by:

\[
R_t = R_{t,t} - R_{x,t}
\]

Level of the Working From Home index on date \( t \), \( WFH_t \) is then given by:

\[
WFH_t = WFH_{t-1} (1 + R_t); WFH_0 = 100
\]

We start the WFH time series in 2015 since the composition of the WFH index is relatively stable after that date. Prior to 2015, many of the companies in the long or short leg were not trading, such as Zoom. Several perturbations on the WFH index construction deliver similar results. Figure C.1 plots the WFH index constructed from weekly and monthly returns. Below we use the monthly return series. The figure cumulates the WFH index returns starting from 100 at the start of 2015.

Figure C.1: Working From Home Risk Factor

Before the pandemic, the WFH factor has modestly positive returns. It then spikes up 50% when the pandemic hits and large parts of the economy transition to remote work. Companies supporting remote work practices (Zoom, Peloton, etc.) flourish, while companies that require
travel of physical proximity sell off (cruise lines, hotels, etc.). The WFH factor spikes up when the pandemic intensifies. It drops sharply when there is news about the development of a vaccine, such as in November 2020, or at the start of 2021. Naturally, the average realized return of the WFH factor during the pandemic is strongly positive.

C.1.3 WFH Risk Exposure

To show that WFH risk emerged in full force during the pandemic, we estimate time-varying betas from 36-month rolling-window regressions for monthly office REIT excess returns:

\[
 r_{t+1}^o - r_t^f = \alpha + \beta_t^m (r_m^{t+1} - r_t^f) + \beta_t^h (r_h^{t+1} - r_t^f) + \beta_t^{wfh} r_{t+1}^{wfh} + e_{t+1}
\]

Figure C.2 shows the estimated betas for office REITS. The patterns in the stock and bond betas of office REITS in the three-factor model (blue line) are similar to those in the two-factor model without the WFH factor (orange line) before the pandemic. However, omission of the WFH factor leads one to overstate the stock market beta during the pandemic (top left panel). The reverse is true for the bond beta in the top right panel.

The WFH beta in the bottom left panel is close to zero prior to the pandemic in February 2020, an exposure estimated over the 36-month window from March 2018 through February 2020. The \( \beta^{wfh} \) for Office REITS declines to around -0.5. It remains strongly negative until the end of our sample at -0.3 in December 2021. The bottom-right panel shows that the \( R^2 \) improved during the pandemic due to the inclusion of the WFH factor.

C.1.4 WFH Risk Price

We estimate the market prices of risk on the WFH factor, \( \lambda^{wfh} \), using the cross-section of 22 individual office REITs listed in Table C.2.

We use a two-stage Fama-MacBeth procedure. In the first stage using the time-series, we estimate 36-month rolling-window regressions of each REIT’s return on the three factor returns;
Table C.1: Composition of WFH Index

Panel A: Long Positions

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<tr>
<th>Ticker</th>
<th>Name</th>
<th>Leg</th>
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<td>Pfizer Inc</td>
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<td>Vaccine Candidates</td>
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<tr>
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<td>UPLD</td>
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Panel B: Short Positions

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<td>Transportation</td>
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<td>UAL</td>
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<td>AAL</td>
<td>American Airlines Group Inc</td>
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<td>LUV</td>
<td>Southwest Airlines Co</td>
<td>Transportation</td>
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<td>CCL</td>
<td>Carnival Corp</td>
<td>Transportation</td>
</tr>
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<td>NCLH</td>
<td>Norwegian Cruise Line Holdin</td>
<td>Transportation</td>
</tr>
<tr>
<td>UNP</td>
<td>Union Pacific Corp</td>
<td>Transportation</td>
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<td>HLT</td>
<td>Hilton Worldwide Holdings In</td>
<td>Hotels</td>
</tr>
<tr>
<td>MAR</td>
<td>Marriott International</td>
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<tr>
<td>CZR</td>
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Table C.2: List of Office REITS

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<td>Alexandria Real Estate Equities, Inc.</td>
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<tr>
<td>Brandywine Realty Trust</td>
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<tr>
<td>Boston Properties, Inc.</td>
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<tr>
<td>CIM Commercial Trust Corp</td>
<td>CMCT</td>
</tr>
<tr>
<td>Cousins Properties</td>
<td>CUZ</td>
</tr>
<tr>
<td>Columbia Property Trust Inc.</td>
<td>CXP</td>
</tr>
<tr>
<td>Easterly Government Properties</td>
<td>DEA</td>
</tr>
<tr>
<td>Equity Commonwealth</td>
<td>EQC</td>
</tr>
<tr>
<td>Empire State Realty Trust</td>
<td>ESRT</td>
</tr>
<tr>
<td>Franklin Street Properties Corp.</td>
<td>FSP</td>
</tr>
<tr>
<td>Highwoods Properties, Inc.</td>
<td>HIW</td>
</tr>
<tr>
<td>Hudson Pacific Properties, Inc.</td>
<td>HPP</td>
</tr>
<tr>
<td>Kilroy Realty Corporation</td>
<td>KRC</td>
</tr>
<tr>
<td>Corporate Office Properties Trust</td>
<td>OFC</td>
</tr>
<tr>
<td>Office Properties Income Trust</td>
<td>OPI</td>
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<tr>
<td>Piedmont Office Realty Trust, Inc.</td>
<td>PDM</td>
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<td>Paramount Group, Inc.</td>
<td>PGRE</td>
</tr>
<tr>
<td>SL Green Realty Corp</td>
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</tr>
<tr>
<td>Vornado Realty Trust</td>
<td>VNO</td>
</tr>
<tr>
<td>Douglas Emmett, Inc.</td>
<td>DEI</td>
</tr>
<tr>
<td>City Office REIT, Inc.</td>
<td>CIO</td>
</tr>
<tr>
<td>New York City REIT, Inc.</td>
<td>NYC</td>
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</table>
i.e., we estimate equation (C.2) for each REIT separately. In the second cross-sectional step, we regress the realized return each month on the betas for that month. The market price of risk estimates are the average of the monthly slope estimates of the second step. We use only the months prior to the onset of the pandemic (December 2014–December 2019) when computing this average. Since the WFH index saw unusually high realizations during the pandemic, inclusion of the pandemic months would lead one to confuse realized with expected returns, while in fact the two are negatively correlated. We obtain $\hat{\lambda}_{WFH} = -7.0\%$ annualized ($t$-stat is -0.52 but the sample is short to reliably estimate this coefficient).¹

The negative market price of risk for WFH risk means that states of the world where the WFH risk factor was large and positive are bad states of the world. This is intuitive, as those are periods

¹Repeating the exercise with weekly instead of monthly return data and the 52-week rolling window betas, we obtain $\hat{\lambda}_{WFH} = -10.2\%$ ($t$-stat is -0.84).
where the coronavirus pandemic surges. Conversely, negative returns to WFH, such as vaccine discovery news (November 8, 2020) are good states of the world.

C.1.5 Expected Returns

For the risk prices on stocks and bond, we use the sample average of the estimated risk premia in the post-1994 period: $\lambda^m = 7.81\%$ and $\lambda^b = 2.91\%$. For the WFH risk price we use $\lambda^{wfh} = -7.0\%$, as estimated above. We combine the three time-varying betas from Figure C.2 with the market price of risk estimates to form the expected return on office REITS as per equation (C.1). Figure C.3 plots the resulting expected return. While the contribution from stocks and bond market risk shrinks over the course of the pandemic, by virtue of the declining stock and bond betas, the contribution from the WFH risk exposure (in purple) is substantial. WFH risk contributes about 2–3% points to the expected return on office during the pandemic.

Figure C.3: Expected Return of Office REITs During Covid

The expected return on office REITs shrinks from 12.86% pre-pandemic (December 2014–December 2019) to 10.79% during the pandemic (December 2019–December 2021), a decline of 207 basis points. In December 2021, the expected return is up to 11.7%.
C.2 Model Derivation

This section contains the full derivation of the model in Section 3.3. The goal is to solve the following equation:

\[
V_t = E_t \left[ \sum_{j=1}^{\infty} M_{t,t+j} (Rev_{t+j} - Cost_{t+j}) \right] = E_t \left[ \sum_{j=1}^{\infty} M_{t,t+j} Rev_{t+j} \right] - E_t \left[ \sum_{j=1}^{\infty} M_{t,t+j} Cost_{t+j} \right] = V_t^R - V_t^C.
\]

First, we solve the revenue side, i.e., for \( V_t^R \).

C.2.1 Revenue

Reproducing the equation for the law of motion for occupied space, \( Q_{t+1}^O \) below:

\[
Q_{t+1}^O (Q_t^O, z') = \min \{Q_t^O (1 - \chi) + Q_t^O \chi s_{t+1}^O (z') + (\tilde{Q}_t - Q_t^O) s_{t+1}^V (z'), \tilde{Q}_{t+1}\}
\]

From the stochastic process of the growth of the total space in the building we get:

\[
\frac{\tilde{Q}_{t+1}}{Q} - 1 = \eta_{t+1}(z') \quad \Rightarrow \quad \tilde{Q}_{t+1} = \hat{Q}_t (1 + \eta_{t+1}(z'))
\]

and the scaled state variable \( \hat{Q}_t^O \), we can be rearranged as

\[
\hat{Q}_t^O = \frac{Q_t^O}{\hat{Q}_t} \quad \Rightarrow \quad Q_t^O = \hat{Q}_t^O \tilde{Q}_t.
\]

To convert \( Q_{t+1}^O (Q_t^O, z') \) as a function of scaled variables, \( Q_{t+1}^O (\hat{Q}_t, z') \), we substitute equations for \( \tilde{Q}_{t+1} \) and \( Q_t^O \),

\[
\hat{Q}_{t+1}^O = \min \{\hat{Q}_t^O \hat{Q}_t (1 - \chi) + \hat{Q}_t^O \hat{Q}_t \chi s_{t+1}^O (z') + (\tilde{Q}_t - \hat{Q}_t^O \tilde{Q}_t) s_{t+1}^V (z'), \tilde{Q}_t (1 + \eta_{t+1}(z'))\}
\]
\[
\hat{Q}_{t+1}^{O} = \min\{\frac{\hat{Q}_{t}^{O} (1 - \chi) + \hat{Q}_{t}^{O} \chi s_{t+1}^{O} (z') + (1 - \hat{Q}_{t}^{O}) s_{t+1}^{V} (z')} {1 + \eta_{t+1} (z')}, 1\}.
\]

Next, the rent revenue in the building/market in period \( t + 1 \) is,

\[
Rev_{t+1}(Q_{t}^{O}, R_{t}^{O}, z') = Q_{t}^{O} (1 - \chi) R_{t}^{O} + \left[ Q_{t}^{O} \chi s_{t+1}^{O} (z') + (\tilde{Q}_{t} - Q_{t}^{O}) s_{t+1}^{V} (z') \right] R_{t+1}^{m}.
\]

\( R_{t}^{O} \) is the average net effective rent per sf on existing leases, and \( R_{t+1}^{m} \) is the market net effective rent per sf on newly executed leases. \( R_{t}^{O} \) is a geometrically-decaying weighted average of all past market rents,

\[
R_{t}^{O} = \chi \sum_{k=0}^{\infty} (1 - \chi)^{k} R_{t-k}^{m}.
\]

Similarly, we can write \( R_{t+1}^{O} \) as,

\[
R_{t+1}^{O} = \chi \sum_{j=0}^{\infty} (1 - \chi)^{k} R_{t+1-k}^{m}
\]

\[
\begin{align*}
R_{t+1}^{O} &= \chi R_{t+1}^{m} + \chi (1 - \chi) R_{t}^{m} + \chi (1 - \chi)^{2} R_{t-1}^{m} + \chi (1 - \chi)^{3} R_{t-2}^{m} + \cdots \\
R_{t+1}^{O} &= \chi R_{t+1}^{m} + (1 - \chi) \left[ \chi R_{t}^{m} + \chi (1 - \chi) R_{t-1}^{m} + \chi (1 - \chi)^{2} R_{t-2}^{m} + \cdots \right] \\
R_{t+1}^{O} &= (1 - \chi) R_{t}^{O} + \chi R_{t+1}^{m}.
\end{align*}
\]

The growth rate of the market’s NER per sqft is a stochastic process, which follows the following law of motion,

\[
\frac{R_{t+1}^{m}}{R_{t}^{m}} - 1 = \epsilon_{t+1}(z') \quad \Rightarrow \quad R_{t+1}^{m} = R_{t}^{m} (1 + \epsilon_{t+1}(z')).
\]

We define the state variable \( \hat{R}_{t}^{O} \) as,

\[
\hat{R}_{t}^{O} = \frac{R_{t}^{O}}{R_{t}^{m}}.
\]
Next, we want to find the law of motion for the scaled state variable \( \hat{R}^O_{t+1} \):

\[
\begin{align*}
\hat{R}^O_{t+1} &= \frac{R^O_{t+1}}{R^m_{t+1}} \\
\hat{R}^O_{t+1} &= \frac{(1 - \chi) R^O_t + \chi R^m_{t+1}}{R^m_{t+1}} \\
\hat{R}^O_{t+1} &= \frac{(1 - \chi) \hat{R}^O_t}{R^m_{t+1}} + \chi \\
\hat{R}^O_{t+1} &= \frac{(1 - \chi) \hat{R}^O_t R^m_{t+1}}{R^m_{t+1}} + \chi \\
\hat{R}^O_{t+1} &= \frac{(1 - \chi) \hat{R}^O_t}{1 + \epsilon_{t+1}(z')} + \chi .
\end{align*}
\]

We define scaled revenues as

\[
\overline{Rev}_{t+1}(\hat{Q}_t^O, \hat{R}_t^O, z') = \frac{Rev_{t+1}}{Q_t R^m_t}.
\]

Rewriting the equation for \( Rev_{t+1}(Q_t^O, R_t^O, z') \) in terms of \( R_{t+1}(\hat{Q}_t^O, \hat{R}_t^O, z') \):

\[
\begin{align*}
Rev_{t+1}(\hat{Q}_t^O, \hat{R}_t^O, z') &= \hat{Q}_t^O \tilde{Q}_t (1 - \chi) \hat{R}^O_t R^m_t + \left[ \hat{Q}_t^O \tilde{Q}_t \chi s^{O}_{t+1}(z') + (\tilde{Q}_t - \hat{Q}_t^O \tilde{Q}_t) s^V_{t+1}(z') \right] R^m_t (1 + \epsilon_{t+1}(z')) \\
Rev_{t+1}(\hat{Q}_t^O, \hat{R}_t^O, z') &= \hat{Q}_t R^m_t \left[ \hat{Q}_t^O (1 - \chi) \hat{R}^O_t + \left[ \hat{Q}_t^O \chi s^{O}_{t+1}(z') + (1 - \hat{Q}_t^O) s^V_{t+1}(z') \right] (1 + \epsilon_{t+1}(z')) \right].
\end{align*}
\]

Scaled Revenue \( \overline{Rev}_{t+1} \) can be written as

\[
\overline{Rev}_{t+1}(\hat{Q}_t^O, \hat{R}_t^O, z') = \hat{Q}_t^O (1 - \chi) \hat{R}^O_t + \left[ \hat{Q}_t^O \chi s^{O}_{t+1}(z') + (1 - \hat{Q}_t^O) s^V_{t+1}(z') \right] (1 + \epsilon_{t+1}(z')).
\]

The expected PDV of revenues is written as

\[
V^R_t = E_t \left[ \sum_{j=1}^{\infty} M_{t+j} Rev_{t+j} \right].
\]
The scaled version of revenues can be written as:

\[ \hat{V}_t^R = \frac{V_t^R}{Q_t R_t^m} \]

which solves the following Bellman equation:

\[ \hat{V}_t^R (\hat{Q}_t^O, \hat{R}_t^O, z) = \sum_{z'} \pi(z'|z) M(z'|z) \left[ \hat{R}e_{t+1} (\hat{Q}_t^O, \hat{R}_t^O, z') + (1 + \eta(z'))(1 + \epsilon(z')) \hat{V}_{t+1}^R (\hat{Q}_{t+1}^O, \hat{R}_{t+1}^O, z') \right] \]

Finally, we get \( V_t^R \) by

\[ V_t^R = \hat{V}_t^R (\hat{Q}_t^O, \hat{R}_t^O, z) Q_t R_t^m. \]

### C.2.2 Costs

The building costs are written as:

\[ Cost_{t+1} = C_{t+1}^{fix}(z') \tilde{Q} + \hat{Q}_t^O C_{t+1}^{var}(z') + \left[ Q_t^O \chi s_{t+1}^O (z') LC_{t+1}^R (z') + (\bar{Q}_t - Q_t^O) s_{t+1}^V (z') LC_{t+1}^N (z') \right] R_{t+1}^m. \]

Substituting for \( R_{t+1}^m \) and \( Q_t^O \), we get,

\[ Cost_{t+1} = C_{t+1}^{fix}(z') \tilde{Q} + \hat{Q}_t^O \hat{Q} C_{t+1}^{var}(z') + \left[ \hat{Q}_t \chi s_{t+1}^O (z') LC_{t+1}^R (z') + (\hat{Q}_t \theta) s_{t+1}^V (z') LC_{t+1}^N (z') \right] R_{t}^m (1 + \epsilon_{t+1}(z')). \]

We define scaled costs as:

\[ \text{Cost} = \frac{Cost_{t+1}}{Q_t R_t^m}. \]

Therefore, we have:

\[ \text{Cost}_{t+1} (\hat{Q}_t^O, z') = C_{t+1}^{fix}(z') + \hat{Q}_t^O \hat{Q} C_{t+1}^{var}(z') + \left[ \hat{Q}_t \chi s_{t+1}^O (z') LC_{t+1}^R (z') + (1 - \hat{Q}_t \theta) s_{t+1}^V (z') LC_{t+1}^N (z') \right] (1 + \epsilon(z')). \]
where

\[ c_{t+1}^{fix}(z') = \frac{C_{t+1}^{fix}(z')}{R_t^m}, \quad c_{t+1}^{var}(z') = \frac{C_{t+1}^{var}(z')}{R_t^m}. \]

The expected PDV of costs is written as:

\[ V_t^C = E_t \left[ \sum_{j=1}^{\infty} M_{t+j} \text{Cost}_{t+j} \right]. \]

The scaled version is:

\[ \hat{V}_t^C = \frac{V_t^C}{Q_t R_t^m}, \]

which solves the Bellman equation

\[ \hat{V}_t^C(\hat{Q}_t^O, z) = \sum_{z'} \pi(z'|z) M(z'|z) \left\{ \text{Cost}_{t+1}(\hat{Q}_t^O, z') + (1 + \eta(z'))(1 + \epsilon(z')) \hat{V}_{t+1}^C(\hat{Q}_{t+1}^O, z') \right\} \]

Finally, we get \( V_t^C \) by

\[ V_t^C = \hat{V}_t^C(\hat{Q}_t^O, z) Q_t R_t^m. \]

### C.2.3 Closed-form solutions

First, we define matrix notations for parameters:

\[ \mathbb{I}_{4x1} = \left[ 1, 1, 1, 1 \right]' \]

\[ E_{4x4} = \left[ \epsilon_{4x1}, \epsilon_{4x1}, \epsilon_{4x1}, \epsilon_{4x1} \right]' \]

\[ H_{4x4} = \left[ \eta_{4x1}, \eta_{4x1}, \eta_{4x1}, \eta_{4x1} \right]' \]

\[ S_{4x4}^O = \left[ s_{4x1}^O, s_{4x1}^O, s_{4x1}^O, s_{4x1}^O \right]' \]
\[ S_{4x4}^V = \begin{bmatrix} s_{4x1}^V, s_{4x1}^V, s_{4x1}^V, s_{4x1}^V \end{bmatrix} \]

Cost Valuation

We first shorthand the expression of \( \overline{C}_{ost_{t+1}}(\hat{Q}_t^O, z') \), which is a linear function w.r.t. \( \hat{Q}_t^O \), as:

\[
\overline{C}_{ost_{t+1}}(\hat{Q}_t^O, z') = a(z') + b(z') \cdot \hat{Q}_t^O
\]

where,

\[
a(z') = c_{t+1}^{fix}(z') + (1 + \epsilon(z')) \cdot s_{t+1}^V(z') \mathcal{L}^N_{t+1}(z'),
\]

\[
b(z') = c_{t+1}^{var}(z') + (1 + \epsilon(z')) \cdot [\chi s_{t+1}^O(z') \mathcal{L}^R_{t+1}(z') - s_{t+1}^V(z') \mathcal{L}^N_{t+1}(z')].
\]

Then, we take the derivative (w.r.t. \( \hat{Q}_t^O \)) of cost valuation Bellman equation:

\[
\frac{\partial \hat{V}_t^C}{\partial \hat{Q}_t^O}(\hat{Q}_t^O, z) = \sum_{z'} \pi(z'|z) M(z'|z) \left\{ b(z') + (1 + \eta(z'))(1 + \epsilon(z')) \frac{\partial \hat{V}_{t+1}^C}{\partial \hat{Q}_t^O}(\hat{Q}_{t+1}^O, z') \right\}
\]

\[
= \sum_{z'} \pi(z'|z) M(z'|z) \left\{ b(z') + (1 + \epsilon(z'))(1 - \chi + \chi s_{t+1}^O(z') - s_{t+1}^V(z')) \frac{\partial \hat{V}_{t+1}^C}{\partial \hat{Q}_t^O}(\hat{Q}_{t+1}^O, z') \right\}.
\]

Notice that the instantaneous reward term, \( b(z') \), is independent to \( \hat{Q}_t^O \). Thus, \( \frac{\partial \hat{V}_t^C}{\partial \hat{Q}_t^O}(\hat{Q}_t^O, z) \) is only a function of \( z \) by checking the valuation in an infinite sum form:

\[
\frac{\partial \hat{V}_t^C}{\partial \hat{Q}_t^O}(\hat{Q}_t^O, z) = \sum_{t=1}^{\infty} \mathbb{E}_t \left[ M(z_{t+\tau}|z) \cdot b(z_{t+\tau}) \right].
\]

Thus, by taking integral of \( \hat{Q}_t^O \), we can conclude that \( \hat{V}_t^C \) is a linear function w.r.t. \( \hat{Q}_t^O \):

\[
\hat{V}_{4x1}^C = a_{4x1}^C(z) + b_{4x1}^C(z) \cdot \hat{Q}_t^O
\]
where,

\[ b_{4x1}^C(z_{4x1}) = \left( I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ \left( 1 - \chi + \chi S_{4x4}^O - S_{4x4}^V \right) \right)_{4x4}^{-1} \cdot \\
\quad \left( \pi_{4x4} \circ M_{4x4} \right)_{4x4} \cdot \left( c_{4x1}^{var} + (1 + \epsilon_{4x1}) \circ \left( \chi s_{4x1}^O \circ LC_{4x1}^R - s_{4x1}^V \circ LC_{4x1}^N \right) \right)_{4x1}. \]

Then, we look back the original valuation function of cost, and equation becomes a linear equation for the only unknown, \( a^C \), and we solve it using the inverse method:

\[ a_{4x1}^C(z_{4x1}) = \left( I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ (1 + H_{4x4}) \right)_{4x4}^{-1} \cdot \\
\quad \left( \pi_{4x4} \circ M_{4x4} \right)_{4x4} \cdot \left( c_{4x1}^{fix} + (1 + \epsilon_{4x1}) \circ \left( s_{4x1}^V \circ LC_{4x1}^N + b_{4x1}^C \circ s_{4x1}^V \right) \right)_{4x1}. \]

**Revenue Valuation**

The revenue valuation problem is very similar to the cost valuation problem, but now the valuation function depends on both \( \hat{Q}_t^O \) and \( \hat{R}_t^O \). So we first look at the Bellman equation for the Bellman equation for \( \hat{Q}_t^O \) or \( \hat{R}_t^O \): \n
\[ \frac{\partial^2 \hat{V}_t^R}{\partial \hat{Q}_t^O \partial \hat{R}_t^O} = d^R(z) \]  \( \text{(C.3)} \)

where,

\[ a_{4x1}^R(z_{4x1}) = \left( I - \pi_{4x4} \circ M_{4x4} \circ (1 - \chi) \circ \left( 1 - \chi + \chi s_{4x4}^O - S_{4x4}^V \right) \right)_{4x4}^{-1} \cdot \\
\quad \left( \pi_{4x4} \circ M_{4x4} \right)_{4x4} \cdot \left( 1 - \chi \cdot S_{4x1} \right)_{4x1}. \]

Next, we integrate equation (C.3) by \( \hat{Q}_t^O \):

\[ \frac{\partial \hat{V}_t^R}{\partial \hat{Q}_t^O} = c^R(\hat{R}_t^O, z) + d^R(z) \cdot \hat{Q}_t^O. \]

Notice that the instantaneous reward term for the Bellman equation for \( \frac{\partial \hat{Q}_t^R}{\partial \hat{R}_t^O} \) is independent to

\[ ^2 \text{We use } \circ \text{ to represent element-wise multiplication for metrics, and } \cdot \text{ for matrix dot product.} \]
\( \hat{R}_t^O: \)
\[
\frac{\partial \hat{R}_t^{\nu_{t+1}}}{\partial R_t^O} = (1 - \chi) \cdot \hat{Q}_t^O. \tag{C.4}
\]

Thus, we can conclude:
\[
c^R(\hat{R}_t^O, z) = c^R(z),
\]
and we can solve \( c^R(z) \) in this linear system:
\[
c^R_{4x1}(z_{4x1}) = (I - \pi_{4x4} \circ M_{4x4} \circ (1 + H_{4x4}) \circ (1 - \chi))_{4x4}^{-1} \cdot
(p_{4x4} \circ M_{4x4})_{4x4} \cdot \left( (1 - \chi) \circ s^V_{4x1} \circ d^R_{4x1} \right)_{4x1}.
\]

Following the same logic, by taking integral w.r.t. \( \hat{R}_t^O \) in equation (C.3) and check the independence of instantaneous reward:
\[
\frac{\partial \hat{V}_t^R}{\partial Q_t^O} = b^R(z) + d^R(z) \cdot \hat{R}_t^O \tag{C.5}
\]
where,
\[
b^R_{4x1}(z_{4x1}) = \left( I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ \left( 1 - \chi + \chi s^O_{4x4} - s^V_{4x4} \right) \right)_{4x4}^{-1} \cdot
(p_{4x4} \circ M_{4x4})_{4x4} \cdot \left( (1 + \epsilon_{4x1}) \circ \left( (\chi s^O_{4x1} - s^V_{4x1}) \circ (1 + \chi d^R_{4x1}) + (1 - \chi) \chi d^R_{4x1} \right) \right)_{4x1}.
\]

Then, we integrate equation (C.4) w.r.t. \( \hat{R}_t^O \) and equation (C.5) w.r.t. \( \hat{Q}_t^O \), we get:
\[
\hat{V}_t^R = a_R(\hat{R}_t^O, z) + c(z) \cdot \hat{R}_t^O + d(z) \cdot \hat{Q}_t^O \cdot \hat{R}_t^O
\]
\[
= a_Q(\hat{Q}_t^O, z) + b(z) \cdot \hat{Q}_t^O + d(z) \cdot \hat{Q}_t^O \cdot \hat{R}_t^O.
\]
By comparing terms, we can conclude
\[
\hat{V}_t^R = a^R(z) + b^R(z) \cdot \hat{Q}_t^O + c^R(z) \cdot \hat{R}_t^O + d^R(z) \cdot \hat{Q}_t^O \cdot \hat{R}_t^O,
\]
and solve the intercept term in the linear system:

\[ a_{4x1}^R(z_{4x1}) = (I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ (1 + H_{4x4}))^{-1} \cdot \\
(\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \left( (1 + \epsilon_{4x1}) \circ \left( V_{4x1}^{\prime} \circ (1 + b_{4x1}^R + \chi d_{4x1}^R) + \chi (1 + \eta_{4x1}) \circ c_{4x1}^R \right) \right)_{4x1}. \]

### C.2.4 Strip Decomposition

The price of a property is the expected PDV of its future cash-flows. By value additivity, this is also the sum of prices of each cash-flow strip:

\[
V_t = V_t^{(1)} + V_t^{(2)} + \cdots = \sum_{j=1}^{\infty} V_t^{(j)} = \sum_{j=1}^{\infty} V_t^{R,(j)} - \sum_{j=1}^{\infty} V_t^{C,(j)}.
\]

The last equality expresses the price of each NOI strip as the difference between the corresponding revenue strip and cost strip, again using value additivity.

The revenue strips can be priced recursively:

\[
V_t^{R,(j)} = \mathbb{E}_t \left[ M_{t,t+j} \hat{V}_t^{R,(j-1)} \right]
\]

starting from

\[
V_t^{R,(1)} = \mathbb{E}_t \left[ M_{t,t+1} Rev_{t+1} \right].
\]

Scaling by potential gross revenue

\[
\hat{V}_t^{R,(j)} = \frac{V_t^{R,(j)}}{Q_t R_t^{m}} = \mathbb{E}_t \left[ M_{t,t+j} \hat{V}_t^{R,(j-1)} (1 + \epsilon_{t+1})(1 + \eta_{t+1}) \right]
\]

starting from

\[
\hat{V}_t^{R,(1)} = \mathbb{E}_t \left[ M_{t,t+1} \hat{Rev}_{t+1} \right]
\]

since

\[
\frac{Q_{t+1} R_{t+1}^m}{Q_t R_t^m} = (1 + \epsilon_{t+1})(1 + \eta_{t+1}).
\]
There is a closed-form expression for each $\hat{V}_t^{R,(j)}$ that can be established using the same procedure we used above to obtain the closed-form solution for the entire claim’s scaled valuation ratio $\hat{V}_t^R$.

$$\hat{V}_t^{R,(j)} = a^{R,(j)}(z) + b^{R,(j)}(z) \cdot \hat{Q}_t^O + c^{R,(j)}(z) \cdot \hat{R}_t^O + d^{R,(j)}(z) \cdot \hat{Q}_t^O \cdot \hat{R}_t^O,$$

for suitably-defined coefficients $a^{R,(j)}(z)$, $b^{R,(j)}(z)$, $c^{R,(j)}(z)$, and $d^{R,(j)}(z)$.

The logic is similar for the scaled price of the cost strips.

$$\hat{V}_t^{C,(j)} = a^{C,(j)}(z) + b^{C,(j)}(z) \cdot \hat{Q}_t^O,$$

for suitably-defined coefficients $a^{C,(j)}(z)$ and $b^{C,(j)}(z)$.

C.3 Calibration Algorithm

The following describes the steps in the calibration algorithm for the universe of NYC office buildings (All NYC) and the subset of A+ buildings (NYC A+). We set the depreciation to 2.7% in both calibrations, a realistic annual depreciation rate for commercial office. The calibration for All NYC takes the persistence parameter of the WFH state, $p$, as given. This parameter is pinned down from the A+ calibration. Conversely, the calibration for NYC A+ takes the parameter $\Delta \eta$ as given. This parameter is pinned down from the All NYC calibration. Hence, the two calibrations are interdependent: they solve a fixed-point problem.

C.3.1 All NYC, given $p$

1. Keep only office buildings and exclude subleases in the CompStak data set of leases for NYC.

2. Calculate the average lease term for all leases in NYC. Set $\chi$ equal to the reciprocal.

3. Estimate $\varepsilon$ from data:
(a) To estimate $\epsilon(E)$ and $\epsilon(R)$, first calculate sf-weighted NER for each month, and take the 6-month moving average. Use data from January 2000 (start of CompStak) until December 2019.

(b) If more than 6 months of the 1-year window falls in recession, then the year is considered to be a recession; otherwise it is considered to be an expansion. Use the leasing cycle definition instead of the business cycle.

(c) Compute the annual growth rate of the six-month moving average, and take the average separately for expansions and recessions.

(d) Estimate $\epsilon(WFH\bar{R})$ as the realized NER growth between December 2019 and December 2020, and $\epsilon(WFH\bar{E})$ as the annualized realized rent growth between December 2020 and May 2022.

(e) Since the values for $\epsilon(E)$ and $\epsilon(R)$ are determined based on the leasing cycle rather than the business cycle, adjust all four $\epsilon(z)$ parameters by a constant so that the unconditional average NER growth in the model, which uses the Markov chain $\pi(z'|z)$ estimated on the business cycle, equals the sample average NER growth.

4. Estimate $\eta(E)$ and $\eta(R)$ from data:

   (a) Compute the growth rate in floor space in year $t$ as the newly constructed office square feet in year $t$ relative to the total square feet of office space built before year $t$ for each year from 1970–2019. This uses the full history of construction years in our CompStak dataset.

   (b) Year $t$ is a recession when more than six months of that year is in recession.

   (c) We take the average the construction growth rate across expansions and recessions.

   (d) Finally, we subtract the rate of depreciation to arrive at $\eta(E)$ and $\eta(R)$.

5. Set $\eta(WFH\bar{E}) = \eta(E) + \Delta\eta$ and $\eta(WFH\bar{R}) = \eta(R) + \Delta\eta$. Find the $\Delta\eta$ such that the long-run...
growth rate of potential rent in the All NYC is zero:

$$\sum_{z} \pi(z)(1 + \varepsilon(z))(1 + \eta(z)) = 1,$$

where $\pi(z)$ is the $4 \times 1$ ergodic distribution of the $4 \times 4$ Markov Chain $\pi(z'|z)$.

6. Estimate the four parameters $\{s^O(E), s^O(R), s^V(E), s^V(R)\}$ to match the following four moments in quarterly Manhattan office occupancy rate data for from 1987.Q1 to 2020.Q1:

(a) empirical mean

(b) empirical standard deviation

(c) empirical min - 0.5%

(d) empirical max + 0.5%

7. Assume that the four parameters $\{s^O(WFHE), s^O(WFHR), s^V(WFHE), s^V(WFHR)\}$ are shifted by a common factor $\delta$ relative to their no-WFH counterparts: $s^{[V,o]}(WFH) = \delta \cdot s^{[V,o]}(no-WFH)$. Estimate the parameter $\delta$ to best fit the dynamics of the office occupancy rate in the nine quarters from 2020.Q2–2022.Q2. These dynamics are given by the model:

$$\hat{Q}^O_{t+1}(\hat{Q}^O_t, z') = \frac{s^V_{t+1}(z')}{1 + \eta_{t+1}(z')} + \hat{Q}^O_t \cdot \frac{1 - \chi \cdot s^O_{t+1}(z') - s^V_{t+1}(z')}{1 + \eta_{t+1}(z')}$$

Simulate the law of motion for occupancy from 1930 until 2019, under the observed sequence of expansions and recessions, to arrive at the initial condition for $\hat{Q}^O$ in 2020.Q1. Next, we simulate the occupancy process forward for the next nine quarters assuming that the first four quarters are WFH-R observations and the last five are WFH-E. We find the $\delta$ that minimizes the distance between the model and the data.
C.3.2 NYC A+, given $\Delta \eta$

The calibration for the A+ office cash flows is based on the subset of leases in A+ buildings. It follows the same steps as outlined above for All NYC, with the following modifications:

3.(d) The observed value for $\epsilon(WFHE)$ in step 3(d) is implausible.\(^3\) We set $\epsilon(WFHE, A+) = \epsilon(WFHE, All) - \epsilon(E, All) + \epsilon(E, A+)$. This preserves the features that A+ market rent growth is less cyclical than All NYC rent growth and that A+ market rent growth in WFH-E is lower than in E.

5. The NYC A+ calibration takes $\Delta \eta$ from the All NYC calibration.

6. We use data from NAREIT on office sector occupancy from 2000.Q1 to 2020.Q1 to calibrate $\{s^O(E), s^O(R), s^V(E), s^V(R)\}$. We target a minimum occupancy rate equal to the empirical minimum—6.5%—because the A+ occupancy data is missing the 1990s, the worst historical period for office occupancy.

8. Given all other parameters, find $p$ to match the observed realized return on NYC-centric office REITS between December 31, 2019 and December 31, 2020, after adjusting for leverage. See the discussion in Section 3.3.4.

Figure C.4 shows the valuation ratio for office $\hat{V}$ conditional on expansion, recession, WFH-expansion and WFH-recession for the All NYC calibration. The x-axis plots the grid for $\hat{Q}^O$ and the y-axis shows the grid for $\hat{R}^O$. Office valuation ratios are increasing in both occupancy $\hat{Q}^O$ and rent premium $\hat{R}^O$.

C.4 Results for NYC A+ Market

Appendix Table C.3 shows the model solution for the A+ calibration. The model delivers a lower cap rate for A+ NYC office, due to the lower riskiness of A+ cash flows. Class A+ has lower

\(^3\)This is not surprising. The data are based on one realization from a transition from WFH-R to WFH-E, which may not be a good measure of the average rent growth conditional on being in WFH-E.
Figure C.4: $\hat{V}$ for All NYC Market by States

State = E

State = R

State = WFH-E

State = WFH-R
vacancy levels than the market as a whole, on average as well as in the WFH states. Appendix Figure C.5 shows the valuation ratio $\hat{V}$ in each state as a function of occupancy and rent state variables.

Table C.3: Model Solution for NYC A+ Calibration

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Uncond</th>
<th>E</th>
<th>R</th>
<th>WFHE</th>
<th>WFHR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cap rate</td>
<td>0.0656</td>
<td>0.0623</td>
<td>0.0828</td>
<td>0.0625</td>
<td>0.0748</td>
</tr>
<tr>
<td>Office $\mathbb{E}[Ret] - 1$</td>
<td>0.0645</td>
<td>0.0516</td>
<td>0.1346</td>
<td>0.0459</td>
<td>0.1184</td>
</tr>
<tr>
<td>Office $\text{RP} = \mathbb{E}[Ret] - 1 - R_f$</td>
<td>0.0496</td>
<td>0.0432</td>
<td>0.0879</td>
<td>0.0375</td>
<td>0.0716</td>
</tr>
<tr>
<td>$\mathbb{E}[g_t]$</td>
<td>-0.0024</td>
<td>-0.0179</td>
<td>0.0989</td>
<td>-0.0289</td>
<td>0.0213</td>
</tr>
<tr>
<td>Vacancy rate = $1 - \hat{Q}^O$</td>
<td>0.0983</td>
<td>0.0819</td>
<td>0.1220</td>
<td>0.1278</td>
<td>0.1553</td>
</tr>
<tr>
<td>$\hat{Rev}$</td>
<td>0.8228</td>
<td>0.8158</td>
<td>0.9340</td>
<td>0.7658</td>
<td>0.8069</td>
</tr>
<tr>
<td>$\hat{Cost}$</td>
<td>0.4228</td>
<td>0.4279</td>
<td>0.4183</td>
<td>0.4114</td>
<td>0.4050</td>
</tr>
<tr>
<td>$\hat{NOI} = \hat{Rev} - \hat{Cost}$</td>
<td>0.3994</td>
<td>0.3874</td>
<td>0.5151</td>
<td>0.3539</td>
<td>0.4013</td>
</tr>
<tr>
<td>$\hat{V}^R$</td>
<td>10.7146</td>
<td>11.0337</td>
<td>10.0413</td>
<td>10.3574</td>
<td>9.3590</td>
</tr>
<tr>
<td>$\hat{V}^C$</td>
<td>4.7105</td>
<td>4.9033</td>
<td>3.9135</td>
<td>4.7601</td>
<td>4.0601</td>
</tr>
<tr>
<td>$\hat{V} = \hat{V}^R - \hat{V}^C$</td>
<td>6.0041</td>
<td>6.1304</td>
<td>6.1278</td>
<td>5.5973</td>
<td>5.2988</td>
</tr>
</tbody>
</table>
Figure C.5: \( \hat{V} \) for NYC A+ Market by States

State = E

State = R

State = WFH-E

State = WFH-R
C.5 Calibration to Other Markets

We repeat the calibration procedure discussed in the main text and in Appendix C.3 for San Francisco and Austin. We use CompStak data to measure market rent growth, $\varepsilon$, before and during the pandemic. We also use CompStak data to measure pre-pandemic office construction rates ($\eta$ is the construction minus the depreciation rate). Like in the NYC calibration, construction rates during the pandemic (WFH-R and WFH-E) are set equal to their pre-pandemic counterparts (R and E) minus an adjustment factor. The adjustment factor for SF (Austin) corrects the NYC adjustment factor for differences between SF (Austin) and NYC in the pandemic-minus-pre-pandemic construction rate change obtained from the Cushman & Wakefield inventory data. Due to the incompleteness of building coverage in CompStak, estimation of $\eta$ for San Francisco and Austin starts from 1980. We use contractual occupancy rate data from Cushman and Wakefield to calibrate $s^O$ and $s^V$ before and during the pandemic. We leave the office depreciation rate and the operational cost parameters the same as in the NYC calibration. Naturally, we assume that the dynamics of the aggregate state variable $\pi(z', z)$ are common across markets, as well as the market prices of risk $M(z', z)$.

Table C.4 shows the calibrated parameters for San Francisco, and Table C.5 shows those for Austin. Tables C.6 and C.7 show the main moments for San Francisco and Austin, respectively. The SF office market is riskier than the NYC market, featuring a rent cycle of greater amplitude which translates into a higher risk premium and cap rate. The opposite is true for Austin. Figure C.6 plots fan charts for occupancy rates, revenues, NOI and cap rates for San Francisco and Austin.

| Table C.4: Calibration for San Francisco |
|-------------------------------|----------------|--------|--------|--------|--------|
| Variable                      | Symbol | E     | R     | WFH-E  | WFH-R  |
| Market NER growth             | $\varepsilon$ | 0.1346 | -0.2130 | -0.0050 | -0.2001 |
| Supply growth                 | $\eta$  | -0.0192 | -0.0101 | -0.0487 | -0.0396 |
| Lease renewal share           | $s^O$   | 0.8500 | 0.6766 | 0.3541 | 0.2819 |
| New leasing share             | $s^V$   | 0.2369 | 0.1948 | 0.0987 | 0.0812 |
Table C.5: Calibration for Austin

<table>
<thead>
<tr>
<th>Variable</th>
<th>Symbol</th>
<th>E</th>
<th>R</th>
<th>WFH-E</th>
<th>WFH-R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market NER growth</td>
<td>$\epsilon$</td>
<td>0.0372</td>
<td>-0.0546</td>
<td>0.0674</td>
<td>-0.0634</td>
</tr>
<tr>
<td>Supply growth</td>
<td>$\eta$</td>
<td>0.0002</td>
<td>0.0076</td>
<td>-0.0071</td>
<td>0.0003</td>
</tr>
<tr>
<td>Lease renewal share</td>
<td>$s^O$</td>
<td>0.9215</td>
<td>0.9215</td>
<td>0.6115</td>
<td>0.6115</td>
</tr>
<tr>
<td>New leasing share</td>
<td>$s^V$</td>
<td>0.2030</td>
<td>0.1000</td>
<td>0.1347</td>
<td>0.0663</td>
</tr>
</tbody>
</table>

Table C.6: Model Solution for San Francisco Calibration

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Uncond</th>
<th>E</th>
<th>R</th>
<th>WFHE</th>
<th>WFHR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cap rate</td>
<td>0.0913</td>
<td>0.0801</td>
<td>0.1320</td>
<td>0.0922</td>
<td>0.1333</td>
</tr>
<tr>
<td>Office $E[\text{Ret}] - 1$</td>
<td>0.1258</td>
<td>0.1028</td>
<td>0.2383</td>
<td>0.1058</td>
<td>0.2063</td>
</tr>
<tr>
<td>Office RP = $E[\text{Ret}] - 1 - R_f$</td>
<td>0.1109</td>
<td>0.0944</td>
<td>0.1916</td>
<td>0.0974</td>
<td>0.1596</td>
</tr>
<tr>
<td>$E[g_f]$</td>
<td>0.0285</td>
<td>-0.0007</td>
<td>0.2245</td>
<td>-0.0281</td>
<td>0.0838</td>
</tr>
<tr>
<td>Vacancy rate = $1 - \hat{Q}^O$</td>
<td>0.1546</td>
<td>0.0992</td>
<td>0.1568</td>
<td>0.3148</td>
<td>0.3462</td>
</tr>
<tr>
<td>$\hat{\text{Rev}}$</td>
<td>0.7735</td>
<td>0.7692</td>
<td>0.9612</td>
<td>0.6475</td>
<td>0.7572</td>
</tr>
<tr>
<td>$\hat{\text{Cost}}$</td>
<td>0.4230</td>
<td>0.4390</td>
<td>0.4237</td>
<td>0.3760</td>
<td>0.3671</td>
</tr>
<tr>
<td>$\hat{\text{NOI}} = \hat{\text{Rev}} - \hat{\text{Cost}}$</td>
<td>0.3505</td>
<td>0.3302</td>
<td>0.5375</td>
<td>0.2715</td>
<td>0.3901</td>
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<tr>
<td>$\hat{V}^R$</td>
<td>7.2999</td>
<td>8.0135</td>
<td>6.6782</td>
<td>5.6732</td>
<td>4.9550</td>
</tr>
<tr>
<td>$\hat{V}^C$</td>
<td>3.4976</td>
<td>3.9494</td>
<td>2.6910</td>
<td>2.7723</td>
<td>2.0816</td>
</tr>
<tr>
<td>$\hat{V} = \hat{V}^R - \hat{V}^C$</td>
<td>3.8023</td>
<td>4.0641</td>
<td>3.9872</td>
<td>2.9009</td>
<td>2.8734</td>
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Table C.7: Model Solution for Austin Calibration

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Uncond</th>
<th>E</th>
<th>R</th>
<th>WFHE</th>
<th>WFHR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cap rate</td>
<td>0.0446</td>
<td>0.0449</td>
<td>0.0562</td>
<td>0.0341</td>
<td>0.0465</td>
</tr>
<tr>
<td>Office $E[\text{Ret}] - 1$</td>
<td>0.0743</td>
<td>0.0534</td>
<td>0.1500</td>
<td>0.0685</td>
<td>0.1844</td>
</tr>
<tr>
<td>Office RP = $E[\text{Ret}] - 1 - R_f$</td>
<td>0.0594</td>
<td>0.0450</td>
<td>0.1033</td>
<td>0.0602</td>
<td>0.1376</td>
</tr>
<tr>
<td>$E[g_f]$</td>
<td>0.0273</td>
<td>0.0248</td>
<td>0.0658</td>
<td>-0.0050</td>
<td>0.0827</td>
</tr>
<tr>
<td>Vacancy rate = $1 - \hat{Q}^O$</td>
<td>0.1493</td>
<td>0.1126</td>
<td>0.1384</td>
<td>0.2619</td>
<td>0.2907</td>
</tr>
<tr>
<td>$\hat{\text{Rev}}$</td>
<td>0.8000</td>
<td>0.8325</td>
<td>0.8669</td>
<td>0.6531</td>
<td>0.6903</td>
</tr>
<tr>
<td>$\hat{\text{Cost}}$</td>
<td>0.4254</td>
<td>0.4360</td>
<td>0.4287</td>
<td>0.3930</td>
<td>0.3845</td>
</tr>
<tr>
<td>$\hat{\text{NOI}} = \hat{\text{Rev}} - \hat{\text{Cost}}$</td>
<td>0.3746</td>
<td>0.3965</td>
<td>0.4382</td>
<td>0.2601</td>
<td>0.3057</td>
</tr>
<tr>
<td>$\hat{V}^R$</td>
<td>17.1823</td>
<td>17.9455</td>
<td>15.4817</td>
<td>16.4288</td>
<td>13.7847</td>
</tr>
<tr>
<td>$\hat{V}^C$</td>
<td>8.8143</td>
<td>9.1314</td>
<td>7.7056</td>
<td>8.8433</td>
<td>7.2517</td>
</tr>
<tr>
<td>$\hat{V} = \hat{V}^R - \hat{V}^C$</td>
<td>8.3680</td>
<td>8.8141</td>
<td>7.7761</td>
<td>7.5855</td>
<td>6.5330</td>
</tr>
</tbody>
</table>
Figure C.6: Fan Charts for San Francisco and Austin

(A) San Francisco: Occupancy

(B) Austin: Occupancy

(C) San Francisco: Revenue

(D) Austin: Revenue

(E) San Francisco: NOI

(F) Austin: NOI

(G) San Francisco: Cap Rate

(H) Austin: Cap Rate