Work From Home and the Office Real Estate Apocalypse[*]

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Abstract

We show remote work led to large drops in lease revenues, occupancy, 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 46% decline in long run value. For all U.S. office markets combined, we find a $556.8 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 financial stability and local public finances.

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1 Introduction

The Covid-19 pandemic ushered in drastic changes in where people work. Physical office occupancy in the major office markets of the U.S. fell to 10% of 2019 levels at the end of March 2020, and has remained depressed ever since, creeping back up to 50% by the end of 2023. In the intervening period, work-from-home (WFH) practices have become ingrained (Barrero, Bloom and Davis, 2021), with many firms announcing permanent remote or hybrid work arrangements and shrinking physical footprints accordingly. These shifts in current and projected future office demand have led to concerns that commercial office buildings may become a stranded asset. 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 not only for institutional investors in the equity of office properties but potentially also for debtholders and financial stability.[1] 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 "urban doom loop" that lowers the quality of life for urban residents and the business climate, and leads to population and employment loss, prompting further declines in property values.

This paper is the first to 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. The value of office reflects the expected present discounted value of its cash flows. We begin by analyzing the shock to cash flows between the end of 2019 and the end of 2023. 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 December 2023. We document a 15.28% decrease in lease revenue in real terms between December 2019 and December 2023 nationwide. Two-thirds of this decline reflects decreases in the quantity of in-force leases, the remainder is accounted for by declines in real rents. The quantity of newly-signed leases falls precipitously over this period. With more existing leases having rolled off than new leases being signed, contractual vacancy rates increased to 40-year-high levels. As

[1] CRE assets make up an important part of the portfolio allocation to "real assets" of a growing number of institutional investors (Goetzmann, Spaenjers and Van Nieuwerburgh, 2021). Investable commercial real estate assets in the United States were worth about $11.68 trillion at the end of 2023. Office represents about $1.78 trillion or 15% of this. There was $5.82 trillion in commercial real estate mortgage debt outstanding at the end of 2023 (Financial Accounts of the United States), comprised of $2.16 trillion in multifamily residential mortgage debt and $3.64 trillion in commercial mortgage debt. Office accounts for about $1.09 trillion of this (17%). Commercial banks were the largest holders of CRE debt with $2.85 trillion (51%). They owned 62% of the commercial and 33% of the multifamily mortgage debt.

of 2024.Q2, 23.6% of office space was available for rent in New York and 34.5% in San Francisco. Rents on newly-signed leases fell by 11.43% in real terms between December 2019 and December 2023 in NYC and by 35.43% in San Francisco. Because a large fraction of leases in force at the end of 2019 did not come up for renewal in 2020, 2021, 2022, or 2023 (55.53% in the U.S., 67.35% in New York), vacancy rates are likely to rise further in years to come, which will likely put severe downward pressure on rents.

We establish a direct connection between firms' remote work plans, measured from corporate announcements on work schedules from the data provider Scoop, and their actual reductions in leased office space. We find that firms that allow their employees to work more days from home have reduced their office space demand by more over the past three years. The same is true for firms with a larger share of remote job postings. We also find that industries and cities with more WFH exposure see larger declines in office demand as measured by occupancy and rents.

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 in the highest rent tier or are built more recently (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 is affected severely both in terms of quantity of new leases and rent levels.

Because most of the office stock is not publicly-traded (and the traded segment disproportionately consists of class A+) 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, we build a novel asset pricing model to infer the changing values.

First, to build intuition, we present a Gordon Growth Model that highlights the large quantitative impact of rent declines on office market valuation. Then, we build a more detailed model which incorporates several important institutional features of commercial real estate assets lacking in the simple model such as long lease duration, leasing risk, market rent risk, and supply growth risk. The model provides a bottom-up valuation too applicable more broadly to assets whose cash flows derive from (overlapping) long-term contracts. A property is a portfolio of long-term leases. We aggregate lease revenues to the property level and subtract costs to arrive at net operating income (NOI). We discount the NOI stream with the stochastic discount factor (SDF) to obtain the property's value. 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. The model conceives of the shift to WFH as a permanent shock. However, there is a transition period during which the economy adjusts to this new reality. The length of this transition period is uncertain.

Our main calibration exercise focuses on the New York City (NYC) office market. The model matches observed market rent, supply, and vacancy dynamics. This includes the sharp increase in office vacancy rates since the end of 2019. The model's SDF is chosen to match the observed risk-free interest rate and the risk premium in the stock market (and their fluctuation across recessions and expansions). A key parameter that affects the change in office valuations is the expected length of the transition period.[2] 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 conduct 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 0.88, indicating that office investors in 2020 believe the transition to last until 2027 (in expectation).

With this parameter in hand, we return to the full NYC office market calibration. Our main result is a 46.7% reduction in the value of the entire NYC office stock between December 2019 and December 2020. Simulating the model forward for eleven 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 in 2026. Since the transition ends with some probability each year, this mean-reversion force pushes office valuations towards an average value in 2030 that is about 46.5% below the 2019 value. Along paths where the economy remains in the WFH transition until 2030, the office stock ends up 66.6% below its 2019 value. Hence, there is substantial uncertainty about future office values that our approach quantifies.

We consider a comprehensive set of robustness exercises to validate our findings and explore the sensitivity of our results to various assumptions. We conduct separate calibration exercises for San Francisco and Charlotte to check the consistency of our results across different office markets. We find larger valuation reductions in San Francisco compared to New York City, consistent with that market being hit harder by remote work, and smaller valuation reductions in Charlotte, which has been a more

[2] This uncertainty about the length of the transition period, governed by this parameter, captures many considerations, including how gradually tenants wish to shrink their footprint—which in turn reflects uncertainty about the effect of WFH on productivity,— how lenient banks are in terms of modifying maturing mortgage loans on under-performing office assets, whether policymakers pass legislation to subsidize office conversions and how long it takes for such measures to become effective, invest in public safety and urban transit, etc.

resilient market. However, both markets see declines, suggesting that spatial reallocation of activity cannot fully explain our results. We also consider robustness exercises which vary the persistence parameter, examine scenarios where WFH transition risk is priced under different risk premiums, test alternative assumptions about market rent growth during WFH periods, and compare against alternate fixed-length WFH transition periods, finding that our key results on large value decreases are robust. We also conduct a counterfactual analysis of intensive margin WFH variation to understand how different hybrid work intensities affect office values.

What do these numbers imply for the aggregate value of the office stock? We calculate a reduction in value of the office stock between the end of 2019 and 2023 of $90.3 billion for NYC, $30.6 billion for San Francisco, and $0.8 billion for Charlotte. For the remaining office markets, we combine market-specific lease revenue declines with valuation ratio changes for NYC to compute the value decline. Nationwide, we find a $556.8 billion decline in office values over the four-year period.

The key takeaway from our analysis is that WFH is shaping up to massively disrupt the value of commercial office real estate in the short and medium term. This conclusion is consistent with our finding that firms appear to demand substantially less office space when they adopt hybrid and remote work practices, and that such practices appear to be persistent. We discuss the implications for financial stability, highlighting the vulnerability of regional banks, and the fiscal health of cities that rely on the tax revenues from commercial properties and the economic activity associated with vibrant downtowns.

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 alternative use. These changes will be interesting to study but are beyond the horizon of our analysis. 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.

Related Literature Our work relates to four literatures. We relate closely to the rapidly growing literature on the measurement of remote work and its impact on real estate, surveyed in Van Nieuwerburgh (2023). Barrero et al. (2021); Bick, Blandin and Mertens (2023); Bartik, Cullen, Glaeser, Luca and Stanton (2020); Aksoy, Barrero, Bloom, Davis, Dolls and Zárate (2022); Brynjolfsson, Horton, Makridis, Mas, Ozimek, Rock and TuYe (2023) measure the prevalence of WFH, including with new survey instruments, tie the bulk of its growth to new work arrangements, and argue that WFH is expected to last. The stability in the share of paid days worked form home in 2022 and 2023 supports this argument. 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 since 2020. Gupta, Mittal, Peeters and Van Nieuwerburgh (2022); Brueckner, Kahn and Lin (2023); Ramani and Bloom (2021); Mondragon and Wieland (2022) study the impact of work from home on residential real estate prices and rents. Ours is the first paper to establish the destructive impact of WFH on the valuation of commercial office properties, and to point out the ramifications for financial stability and local public finance.

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, Kichko, Matheson and Thisse, 2022; Monte, Porcher and Rossi-Hansberg, 2023). These models are well-suited for thinking about long-run implications of remote work on city structure, including how space could be adaptively reused. This paper uses micro data on office leases to document changes in commercial real estate markets with the rise in remote work, and uses these data as inputs in a new asset pricing model. The finance perspective, which focuses on risk and transition dynamics, is a useful complement to the urban economics perspective. An important challenge for future work is to integrate these two approaches.

Our work relates to a literature examining commercial real estate as an asset class. Cvijanović, Milcheva and van de 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 with cash flows stipulated in long-term, renewable contracts.

Finally, a strain of finance 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, 2019; Barnett, Brock and Hansen, 2020; Pástor, Stambaugh and Taylor, 2022; Eisfeldt, Schubert and Zhang, 2023). We contribute to this literature by documenting a novel disruptive shock in the form of remote work, and highlighting exposure of urban commercial real estate assets to this risk factor. We consider uncertainty about the length of the transition period and its impact on cash flows in our benchmark model, and consider an extension in which this uncertainty is also a separate priced risk factor.

The rest of the paper is organized as follows. Section 2 discusses changes in the office leasing market in the 2020–2023 period, highlighting the contemporaneous losses to lease revenue, and identifying remote work as the key driver. These stylized facts present key targets for the model in Section 3, which develops a novel asset pricing model to connect shocks to the office market with the valuation of office properties. Section 4 discusses the outcomes of the model for our main calibration to NYC, as well as different property segments and other geographies. Section 5 concludes with a discussion of the implications for financial and fiscal fragility. The appendix contains additional empirical results and model details.

2 The Impact of WFH on the Office Market

2.1 Data

In comparison to other real estate markets, such as residential real estate, the market for commercial office buildings is relatively 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 commercial real estate leases in the U.S. for the period January 2000–December 2023. The company sources leasing data from a large network of commercial brokerage and appraisal firms. Data coverage improves in the first part of the sample and stabilizes around 2015. CompStak leasing data separates different property types, and we focus on office leases. This comprises buildings used for conducting business activities and professional services, with space typically allocated towards administrative work, meetings, client services, and other essential building functions.

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, and lease type (new lease, extension, expansion). Building characteristics include: location, quality (class A, B, or C), age, market, and submarket. Tenant characteristics include: name, industry (SIC and NAICS code), employees, and ticker (if publicly traded). We use this data to study the evolution of the lease market over the past decade, in terms of quantities, prices, and contract features.

We augment the CompStak data with city-level vacancy information from Cushman & Wakefield. Cushman & Wakefield is one of the largest commercial real estate brokerage firms in the United States collecting information on leasing characteristics across 90 office markets. Their data track 5.6 billion square feet of office real estate by inventory, enabling comprehensive analysis of office vacancy and leasing trends across cities. Appendix A1 compares the Compstak to the Cushman & Wakefield data.

In public markets, we obtain monthly returns for all office REITS included in the National Association of Real Estate Investment Trust (NAREIT) office index for the period 2019–2023.

To measure remote working conditions at the firm level, we use information from Scoop, which provides a Flex Index containing information on the full time, hybrid, and fully remote working practices of over 3,000 firms with a combined 42 million employees. The Flex Index is the most comprehensive source on company office requirements, with information on office policies sourced from a combination of public corporate statements and crowd-sourced information by employees. This data source allows us to measure remote working plans by office tenants and connect them to their leasing decisions. This is in contrast to most survey-based approaches, which typically ask workers about their remote working status. Our focus is on firms and their space choices, so we need specialized information on working arrangements at the company level. We also explore a remote job postings measure drawn from Ladders, an online job search service site.

2.2 Shock to Leasing Revenue

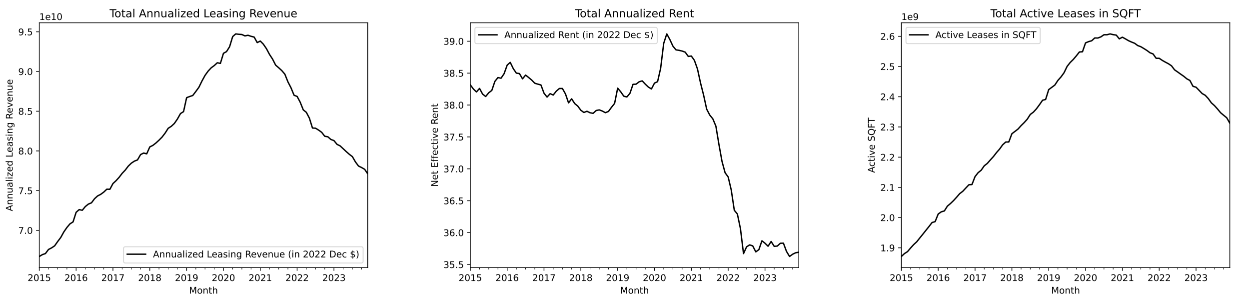
We begin by highlighting the reduction in current leasing revenue. The total value of annualized leasing revenue on *in-force* office leases across all 105 U.S. office markets was $91.02 billion in December 2019 (all numbers expressed in December 2022 dollars). Total leasing revenue declined by 15.28% nationwide, falling to $77.11 billion in December 2023. This decline is substantial in light of the long-term nature of office leases. It indicates large shifts in leasing activity among those tenants in a position to make a choice about their office space needs. Figure 1, Panel A, plots the time series of total leasing revenue.

This decline can be separated into the changes to rents and to quantities. Throughout the paper, we use the concept of net effective rent (NER).[3] Most leases in force in 2020–23 were signed before 2020 and have built-in nominal rent escalation clauses. However, the scheduled rent increases were not large

[3]The NER augments 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.

Figure 1: Revenues on In-Force Leases

Panel A: Revenue | Panel B: Rent | Panel C: Quantity



Notes: The graph shows the time series of annualized lease revenue (Panel A), rent per square foot (Panel B), and total leased space in square foot (Panel C) for in-force leases. Revenues and rent are expressed in December 2022 dollars. Data are sourced from CompStak.

enough to keep pace with inflation, leading to a real NER drop on in-force leases of 6.69% (Panel B of Figure 1). This rent decline also reflects reductions in the NER on *newly-signed* leases. Nationally, the NER fell by 8.59% in 2020. Starting in early 2021, the NER on new leases experienced a partial reversal, only to continue the downward trend in 2022 and 2023 (see Appendix Figure A2).

The quantity of in-force leases (in square feet) fell by 9.27% between December 2019 and December 2023 (Panel C of Figure 1). 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. Figure A3 confirms a substantial decline in the volume of newly-signed leases. The evidence suggests that understanding the quantity dimension is of utmost importance when it comes to understanding shocks to office cash flows.

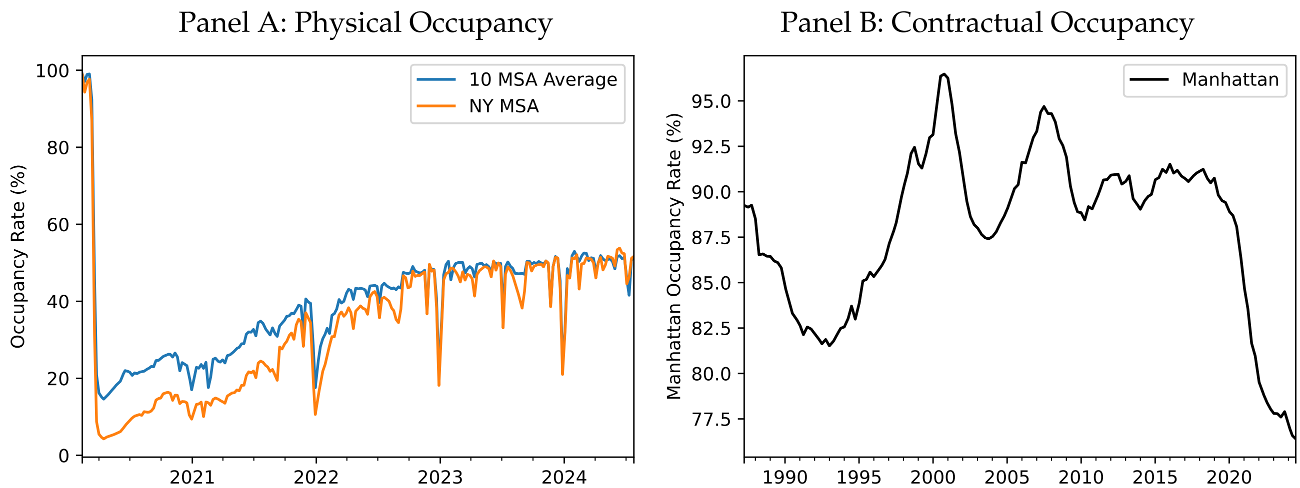
2.3 Physical Occupancy, Contractual Occupancy, and Lease Expiration

Figure 2 (Panel A) highlights 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. The Kastle data covers more than 2,600 buildings and 41,000 businesses in 138 cities.[4] Over the course of 2020, about 70% of college-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% in

[4] Appendix A4 provides more details on Kastle and alternative measures of physical office occupancy. Other data sources, such as public transit usage, trips to the central business district from Safegraph cellphone data (Monte et al., 2023), or survey data line up well with the Kastle data. Barrero, Bloom and Davis (2023) provide a review of the literature on measuring WFH practices, finding that days worked from home account for as much as 28 percent of paid workdays among Americans 20–64 years old. Because WFH practices are concentrated among white-collar workers with the capacity to work in office settings, they have particularly large impacts on the physical presence of such workers in office buildings.

NYC) by the end of 2020. The return to the office proceeded with fits and starts in 2021, but began to stall in mid-2022. The latest data as of July 24, 2024 show a 51.1% occupancy rate among the largest 10 office markets (51.7% in NYC). After four years of remote work, many employers and employees have formed new habits and expectations. Employees report valuing the ability to WFH. Employers have revised upward their own longer-run expectations on average employee days worked from home (Barrero et al., 2021; Aksoy et al., 2022), and have begun to adjust their demand for office space, as shown in more detail below.

Figure 2: Office Occupancy

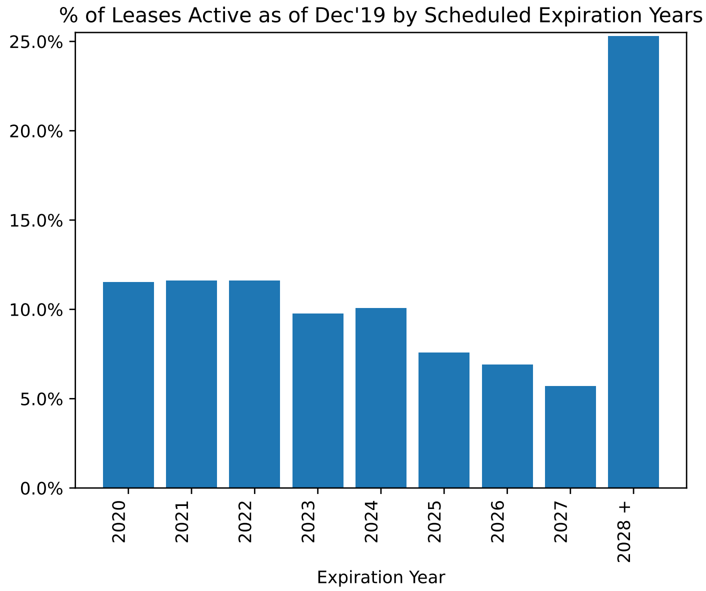


Notes: Panel A shows office physical office occupancy measured from turnstile data for the New York metropolitan area and the panel of 10 metropolitan areas covered by Kastle. Panel B shows contractual office occupancy for Manhattan, sourced from Cushman & Wakefield.

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 gradual reaction is the staggered nature of commercial leases, highlighted in Figure 3. 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 44.47% by square feet came up for renewal in 2020, 2021, 2022, and 2023 combined. Nearly all of the 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 remains highly uncertain, yet is a crucial determinant of office valuation.

Despite the modest share of tenants that have seen lease expirations so far, we already observe drastically higher vacancy rates reflecting lease non-renewals and partial renewals among that sample. The contractual occupancy rate in Manhattan, the country's largest office market, was at a 40-year low of

Figure 3: Lease Expiration Schedule



Notes: The figure shows the percentage of leases expiring per year in square feet for leases that were in force as of December 2019. Data are sourced from CompStak and are for all U.S. office markets.

76.4% in the second quarter of 2024, as shown in Panel B of Figure 2. In San Francisco, contractual occupancy fell dramatically, from 95% at the end of 2019 to 65% in 2024.Q2.

Taken together, this evidence points to further occupancy and cash-flow declines in years to come, as more leases come up for renewal.

2.4 Flight to Quality

The adoption of WFH does not affect all offices equally. The highest-quality buildings, class A+, which we define as those either in the top-10% of rents or those recently built, fare much better in terms of net effective rents.[5] Indeed, our model below will confirm the milder impact of WFH on A+ office valuations.

Figure 4 illustrates this “flight to quality" by plotting the relationship between building quality and NER for all NYC and San Francisco office leases. The NER is residualized with respect to month, submarket, and tenant fixed effects, so as to control for shifting geographic or tenant composition.[6] Panel A

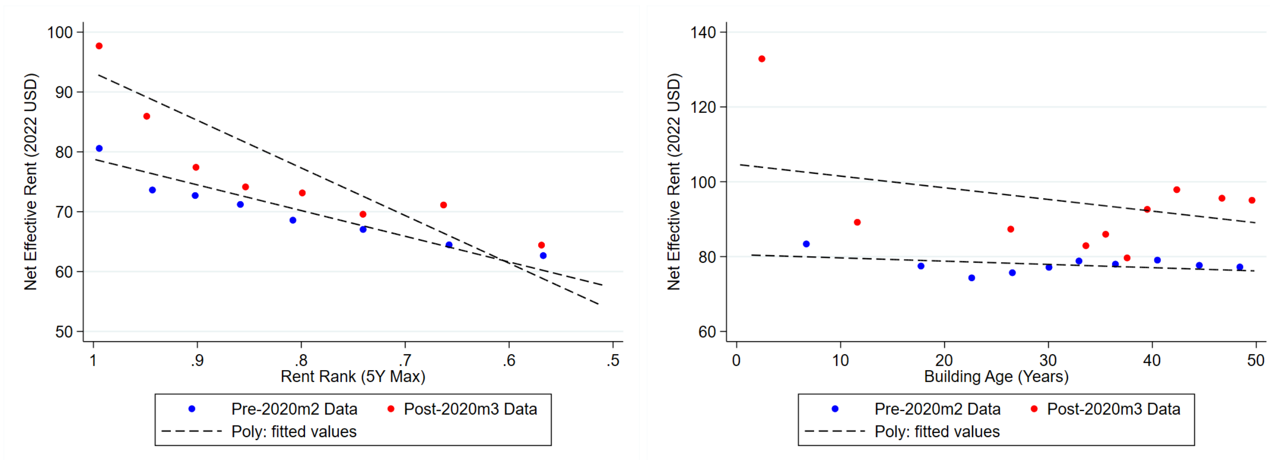
[5]Specifically, we isolate leases that are either (1) in the top-10% of the NER distribution in each quarter and submarket among all properties that are ranked as Class A by CompStak or (2) are younger than 5 years. For the first “high rent" criteria, we categorize a building that has such a lease as A+ and assume that the A+ status remains for five years, unless another top-10% lease is signed in that building at which point the five-year clock resets. We pause new high-rent-criteria-based entry into the A+ group after December 2019 to avoid self-selection in the “flight-to-quality" effect. By this definition, 26.9% of square feet and 34.4% of lease revenue is in A+ office buildings in New York City. The resulting 61.5 million square feet of A+ office space is very close to the 60 million square feet of “trophy" office buildings on the NYC property tax rolls.

[6]The results without tenant fixed effects are similar, and if anything, stronger.

Figure 4: Building Quality and Changes in Rents

Panel A: By Building Rent Rank

Panel B: By Building Age



Notes: The graph shows the changing gradients of building quality and commercial rents, before and after the beginning of the pandemic for NYC and San Francisco. Quality is measured by building building rent rank (Panel A) or by age (Panel B) and the, the highest ranking that any lease in a building had in the previous five years. Our definition of "A+" buildings corresponds to those in the top ten percentile of this rent rank (Panel A) and those younger than five years. To estimate these specifications, we first residualize all office lease data in NYC and San Francisco against the commencement month of the lease, a tenant fixed effect, and a submarket fixed effect. We then plot the residuals from that regression (adding back the average level of rents) separately for pre-pandemic (February 2020 and before, in blue) and the post-pandemic data (March 2020 and after, in red) as binscatters with ten bins following Cattaneo, Crump, Farrell and Feng (2024). Data are sourced from CompStak.

sorts office properties by their rent rank, with 0.9 indicating the 90$^{\text{th}}$ percentile of the NER distribution. We find a strong association between building quality and rents in the cross-section, consistent with the general role for filtering (Baum-Snow, Heblich and Rosenthal, 2022). Interestingly, we find a steeper gradient after March of 2020. Quality becomes a more highly-valued attribute after the onset of WFH. Time series evidence in Figure A5 confirms the diverging dynamics of NER between the A+ segment and the remaining segments (classes A-, B, and C) in both the national and NYC samples.

Panel B of Figure 4 sorts buildings by age rather than rent rank. Again, we find a strong NER-age gradient, which steepens after the widespread adoption of WFH. NERs for the newest buildings are higher after March 2020 than before. Figure A6 confirms these NER dynamics in the time-series. It also shows stronger occupancy dynamics for A+ buildings than all others over the 2020–23 period.

Appendix Table A2 provides a more formal regression evidence estimating the negative relationship between building age and NER, after controlling for month, submarket, tenant, and even building fixed effects. We estimate an additional 3.9% point rent elasticity to age after March 2020 versus before, which is economically and statistically significant. This association is stronger in major markets, especially in NYC and San Francisco.

2.5 Connecting Remote Work and Office Demand

This section examines how remote working policies have impacted office demand. While some employers have adopted fully remote working models, a larger fraction have shifted to hybrid work (Bloom, Han and Liang, 2022), in which employees split time between home and office. The implications of hybrid work for office demand are less clear than for fully-remote positions as some office presence is still required. However, firms may still optimize space usage through strategies like staggered schedules, consolidating office presence, or flexible arrangements such as hot-desking and hoteling.

We measure remote work practices using the Scoop data which provides firms' return-to-office plans as of the end of 2022 for a sample of over 3,000 firms. We sort these firms by the number of workdays that employees are required to be present in the office in a typical week. While return-to-office plans remain in flux, our classification provides an estimate of firms' expected office plans at a time that they are making important choices on physical footprint. We merge tenants' WFH plans from Scoop with firm-level changes in office demand from CompStak, measured as the percentage change in active lease space in square feet from December 2019 to December 2023 across all the tenants' locations in the U.S. Tenants have a more negative change in office demand if they do not renew leases that come up for renewal during this period or if they renew and take less space.

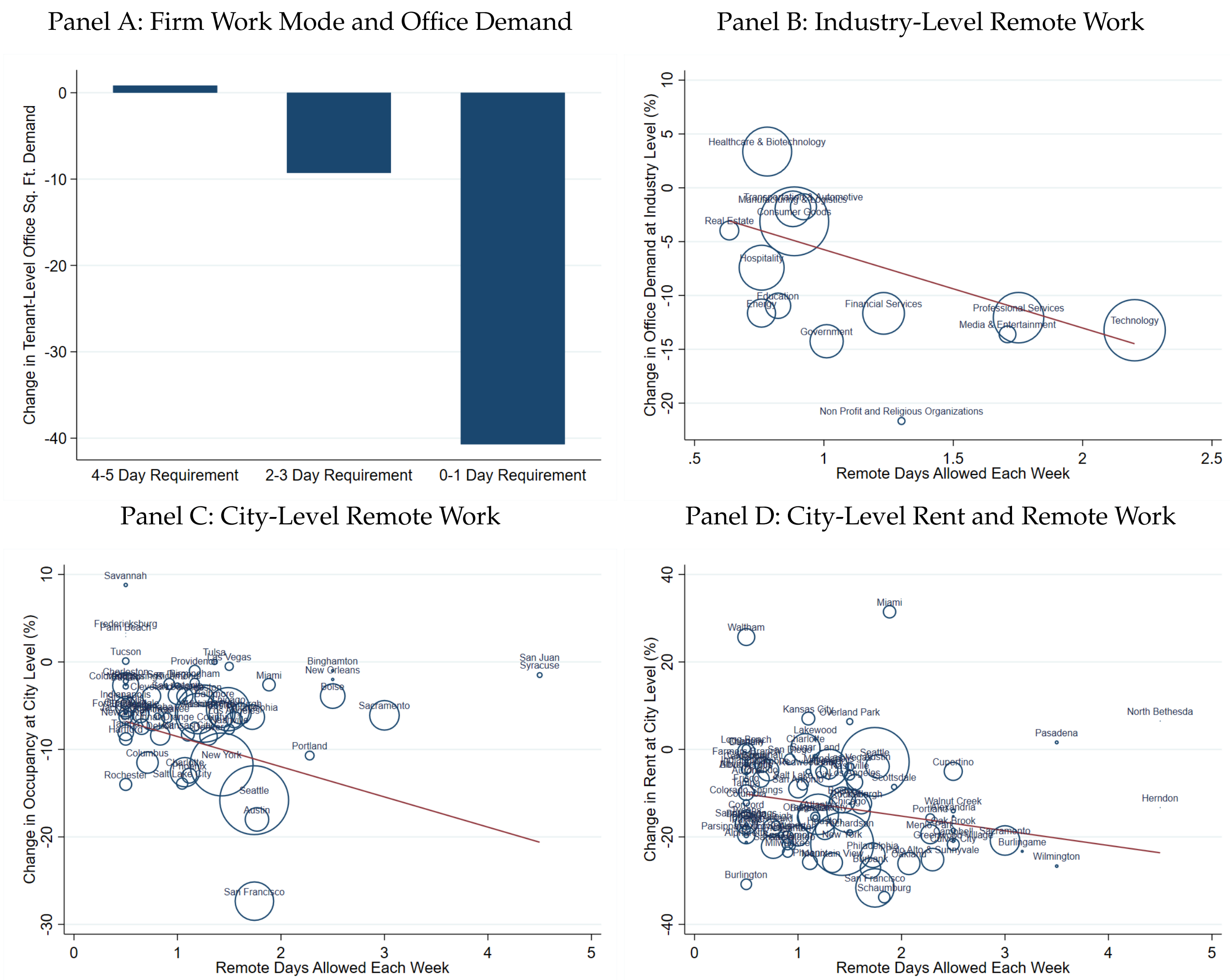
Panel A of Figure 5 shows that hybrid work is strongly associated with lower office space demand. Firm-level office demand increases by 1% for firms whose employees are expected in the office 4 or 5 days per week, decreases by 9% for tenants whose workers will be on site 2-3 days, and decreases by 41% for tenants whose workers are expected to be in the office only 1 day per week or fully remote. Tenants have prior lease commitments that remain in force over the period over which we compute the change in office demand, so that even tenants that have gone fully or mostly remote likely have not fully adjusted their office demand by the end of 2023. These results are therefore likely to understate the long-term impacts of remote work practices on firm office demand. Indeed, we observe larger effects when we weight firms based on their observed leasing footprint in 2019 (see Figure A7).

We also examine the relationship between remote plans and office demand at higher levels of aggregation. We use tenant industry codes to aggregate both tenant office demand and WFH plans to the industry level. Panel B of Figure 5 shows a strongly negative relationship, with industries such as technology that are more remote showing much larger declines in office demand relative to industries such as healthcare which require more in-person presence.

We also find a negative relationship between WFH plans and office demand at the city level in Panel

C, where we use changes in office occupancy from Cushman & Wakefield to capture city-level office demand. While the relationship is slightly weaker than at the industry-level, we find that cities such as San Francisco which have more remote work see larger decreases in overall city-level occupancy, suggesting again that remote work appears to be driving cross-sectional differences in office demand.

Figure 5: Hybrid Work and Office Demand



Notes: Panel A shows the relationship between firm space demand and stated back-to-work office plans. We measure firm space demand by comparing the firm's total leased square footage in December 2023 against the amount pre-pandemic in December 2019 using CompStak data. We then calculate the firm's back to office plans by using Scoop data on firm remote plans. We sort these by assessing how many days a week the firm anticipates workers being back in the office: 0–1 (close to fully remote positions), 2–3 days/week, and 4–5 days a week (including fully in person requirements). Panel B shows the relationship between industry-level remote work and industry-level firm demand, aggregating both the WFH plans and office demand to the industry level. Panel C shows the relationship between city-level remote work and city-level change in overall occupancy level drawn from Cushman & Wakefield. We compare the occupancy ratio between 2023Q4 and 2019Q4. Panel D shows the relationship between city-level remote work and city-level average rent change from 2019 to 2023 in CompStak change in market rent from CompStak. We remove the tenant industry, renewal, and submarket fixed effects from the deflated net effective rent, and then weight by transaction sq. ft. to calculate the average rent.

Panel D shows the negative relationship between city-level remote work plans and the change in city-level average NER between 2019 and 2023 in CompStak data. Not only quantities but also prices change in the cross-section of WFH intensity.

Table A3 provides the estimates which correspond to this figure. At the firm-level, each additional two days of remote work per week leads to a nearly 21 percentage point decline in office space (column 1).[7] We also observe this relationship at the industry and city levels, with each additional two days of remote work leading to a reduction in space demand by 15 percentage points at the industry level (column 2) and 7 percentage points at the city-level (column 3). Each additional two days of remote work will also lead to a reduction of 7 percentage points in average rent at the city-level (column 4).

As an alternative measure of firms' WFH plans, we measure the fraction of a firm's job listings that are for fully-remote positions from Ladders. Table A4 finds a 10% point increase in the share of remote job postings lowers office demand by 3.9–4.9% points.

Combined, our empirical results show that office space demand has declined considerably over the course of the post-2020 period and that changes in remote work policies appear to be driving this trend. Firms that have low on-site work requirements or post more fully-remote job openings experience larger declines in office demand. Decreases in office demand are still substantial among firms with hybrid back-to-office plans, suggesting that even hybrid work plans pose major disruption to aggregate office demand, with significant implications for aggregate office values. Section 4.4 uses the model to study the impact of intensive-margin variation in WFH, disciplined by the estimated relationship at the city level between WFH plans and changes in occupancy and rents.

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 develop a valuation model. We start with a simple back-of-the-envelope calculation, before moving on to a richer valuation model.

3.1 Back of the Envelope

It is instructive to start with a very simple model for the value of the office stock. The simplest valuation model is the Gordon Growth model. It is a dividend discount model that assumes constant cash-flow growth rate G and a constant discount rate R to compute the present value of future cash flows. Specif-

[7] The remote work index is a three point scale, so a one unit increase corresponds to an increase in two days a week remotely for a firm going from 0–1 allowable remote days to 2–3, or from 2–3 days to 4–5 days a week.

ically, the valuation ratio of prices V relative to current cash flows D is given by:

$$\frac{V}{D} = \frac{1}{R - G}.$$

This is a useful model to think of the steady-state in the office market, describing both the situation before 2020 with low incidence of working from home and the new steady state, at some future date, when all the transitional dynamics and economic adjustments to the new world with high incidence of WFH have fully played out. Moreover it seems reasonable to assume that the new and old steady states share the same long-run growth in cash flows G and discount rate R, and hence the same valuation ratio. After all, it is not clear why the mean or the riskiness of long-run office cash flow growth rates would be permanently affected once the supply and demand for office have re-equilibrated. Under these assumptions, the value decline in the office market due to an unexpected shift from a world with low-WFH uptake to one with permanently higher-WFH uptake, ΔV, is fully captured by the decline in cash flows during the transition period, ΔD:

$$\Delta \log V = \Delta \log(V/D) + \Delta \log D = 0 + \Delta \log D = \Delta \log D.$$

A simple back-of-the-envelope approach to quantifying ΔD is to use the decline in real office rent revenue, observed between the end of 2019 and the end of 2023 (Figure 1) of 15.28%, and to combine it with the fact that only 44.47% of pre-2020 leases (as a share of total dollars of leasing revenue) came up for renewal over this period. Applying the same rent decline to the remainder of the leases that have yet to come up for renewal would result in a total cash-flow and office value decline of 15.28%/44.47%=34.36% nationwide. The same calculation for the New York City office market would deliver a value decline estimate of 12.56%/32.65% = 38.47%.

These calculations make several simplifications. They assume that revenue and net cash flow (revenue minus expenditure) growth change proportionately, which is not a good assumption in the presence of fixed costs. They ignore the fact that the cash flow drop occurs over a number of periods and should be discounted back properly. They ignore the dynamics of leasing revenues, which depend on the subtle interplay of the evolution of occupancy, average in-place rents, and market rents. They ignore that the transition may be accompanied by reduced new office construction and by office conversion to alternative use, both of which shrink the aggregate office stock. Maybe most importantly, they ignore the uncertainty in the length of the transition period during which the economy suffers from lower lease renewal rates, vacancy fill rates, rent growth, and supply growth. For these reasons, we now turn to a richer model of the transition period.

3.2 A Richer Model of the Transition Period

We now build a model where the initial transition in 2020 from a low-WFH to a high-WFH world was a probability-zero event (an MIT shock) from the pre-2020 vantage point. Once, the shift occurred, however, the new high-WFH world became permanent. Like in the simple model from the previous section, we assume that the shift from a low-WFH to a high-WFH world in 2020 permanently lowers the demand and supply of office space. Once the office market reaches its new steady-state equilibrium, the valuation ratio (the value of $1 of office cash flows) is the same in the new steady-state as it was in the old pre-2020 steady state.

The difference with the simple model is that the decline in the value of the office stock now depends on the cash flow dynamics in a transition period, during which the economy gradually adjusts to this new, permanent reality. During this transition period, office tenants whose leases expire "right-size" their office demand through temporary reductions in lease renewal rates. Office vacancy fill rates, rent growth rates, and rates of net new office supply (new construction minus supply reduction through office conversion to alternative use) are all temporarily lower. This transition period may take several years as the excess inventory of offices needs to be "worked off" until supply and demand in the office market are back in equilibrium.

The length of this transition period is *uncertain*.[8] The longer the transition lasts, the larger the hit to office values. The parameter p governs the expected length of the transition. In each year of the transition, the economy remains in the transition regime for one more year with probability p and exits the transition to the new steady state with probability $1 - p$.

The richer model captures several real-world features of the property's cash flows which makes this valuation non-standard, relative to the valuation of 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 in-place leases. The leases are finite, but there is additional rental revenue after the leases mature. After some initial vacancy, tenant improvements, and conces-

[8]While not explicitly modeled, this uncertainty captures many considerations, including how gradually tenants wish to shrink their footprint, which in turn depends on evolving perceptions of the relative productivity of in-office versus work from home, how forceful lenders are in terms of forcing an early resolution of non-performing office mortgages, whether and how fast policymakers pass legislation to subsidize office conversions and how long it takes for such measures to be effective, how much taxpayers invest in public safety and urban transit to reinvigorate downtowns, etc.

sions (e.g., free rent) the space can be released at the market rent. The building may not be fully leased, in which case vacancy creates cash flow shortfalls. On the cost side, the operating expenses include a provision for regular capital expenditure and maintenance. A part of the costs is fixed, while a part varies with occupancy. The presence of fixed costs creates operating leverage. Costs also include leasing commissions, which are different for new leases and lease renewals. Finally, supply growth affects the overall size of the office market.

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. This model should be useful for valuing income-generating assets in any sector or location. Section 3.3 describes a model calibration focused on the NYC office market.

The value of a building (or portfolio of buildings or the market overall) is the expected present discounted value of rent revenues Rev_{t+j} minus expenditures $Cost_{t+j}$:

$$\begin{aligned} V_t &= E_t\left[\sum_{j=1}^{\infty} M_{t,t+j}\left(Rev_{t+j} - Cost_{t+j}\right)\right] = E_t\left[\sum_{j=1}^{\infty} M_{t,t+j} Rev_{t+j}\right] - E_t\left[\sum_{j=1}^{\infty} M_{t,t+j} Cost_{t+j}\right] \\ &= V_t^R - V_t^C \end{aligned} \tag{1}$$

where $M_{t,t+j}$ is the cumulative stochastic discount factor (SDF) between t and $t+j$, which provides the time-t present value equivalent of an uncertain cash flow at time $t+j$. V_t is an end-of-period (ex-dividend) price. By additivity, the value of the building is the difference between the value of the (positive) rents minus the value of the (positive) costs.[9]

3.2.1 Modeling Revenues

The central challenge in modeling leases is incorporating the process of lease expiration and renewal. This is important because commercial leases are long-term in nature, but have shorter duration than the expected life of the building. In our model, leases comes due in the current period with probability χ.[10] The random arrival of lease expiration absolves us from having to keep track of the history of past lease executions.

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

[9] This gets around the issue that the difference between revenues and costs (before-tax net cash flow) can be negative.

[10] Under the law of large numbers, χ is also the share of all leases coming due in a given period. This interpretation is appropriate when valuing the office stock of an entire city.

a building/market is:

$$Q^O_{t+1} = \min\left\{Q^O_t(1-\chi) + Q^O_t \chi s^O_{t+1}(z') + (\overline{Q}_t - Q^O_t)s^V_{t+1}(z'), \overline{Q}_{t+1}\right\}.$$

The first term represents occupied space not up for renewal. The second term captures renewals, where $s^O_{t+1}(z')$ is the stochastic renewal rate, combining extensive and intensive margins of renewal. The third term represents newly rented previously vacant space, with $s^V_{t+1}(z')$ as the stochastic share of vacant space being rented, including expansions. This share is unbounded above to allow for market growth.[11]

The growth in available space in a building/market, which reflects new construction (renovation of a building that adds floor space or new construction in a market) net of depreciation, follows the stochastic process:

$$\frac{\overline{Q}_{t+1}}{\overline{Q}_t} - 1 = \eta_{t+1}(z').$$

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

$$Rev_{t+1} = Q^O_t(1-\chi)R^O_t + \left[Q^O_t \chi s^O_{t+1}(z') + (\overline{Q}_t - Q^O_t)s^V_{t+1}(z')\right] R^m_{t+1},$$

in which R^O_t is the average net effective rent per square foot on existing leases and R^m_{t+1} is the market's net effective rent (NER) per square foot on newly executed leases. The NER incorporates concessions (free rent) and tenant improvements. We assume that all new leases are signed at the market NER.

The growth rate of the market's NER per square foot follows the stochastic process:

$$\frac{R^m_{t+1}}{R^m_t} - 1 = \epsilon_{t+1}(z').$$

Define potential rent as the rent revenue based on full occupancy at the prevailing market rent: $\overline{Q}_t R^m_t$. Scale the expected present discounted value (PDV) of lease revenues V^R_t from (1) by potential rent to obtain a valuation ratio: $\hat{V}^R_t = \frac{V^R_t}{\overline{Q}_t R^m_t}$. This "price-dividend" ratio of the lease revenue claim solves a Bellman equation, spelled out in Appendix B.

[11] Space that became vacant at the end of the previous period and is immediately re-rented in the current period is captured by the s^O process.

3.2.2 Modeling Costs

Costs include operating expenditures, capital expenditures, and leasing commissions. Tenant improvements and concessions are already reflected in net effective rents. We divide these into fixed costs ($C^{fix}t$), which include occupancy-independent expenses like property insurance and taxes, as well as the fixed cost of utilities and maintenance, and the per-period equivalent of capital expenditures. Variable costs ($C^{var}t$) depend on occupancy. Leasing commissions, higher for new leases than renewals ($LC^N > LC^R$), are proportional to first-year rental revenue.

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

$$Cost_{t+1} = C^{var}_{t+1}(z')Q^O_{t+1} + C^{fix}_{t+1}(z')\overline{Q}_{t+1} + \left[Q^O_t \chi s^O_{t+1}(z')LC^R_{t+1}(z') + (\overline{Q}_t - Q^O_t)s^V_{t+1}(z')LC^N_{t+1}(z')\right] R^m_{t+1}.$$

Let the cost per square foot, scaled by effective rent per square foot, be defined by lowercase letters:

$$c^{fix}_{t+1}(z') = \frac{C^{fix}_{t+1}(z')}{R^O_{t+1}} \;\; and \;\; c^{var}_{t+1}(z') = \frac{C^{var}_{t+1}(z')}{R^O_{t+1}}.$$

Scale the expected PDV of costs V^C_t from (1) by potential rent to obtain a valuation ratio: $\widehat{V}^C_t = \frac{V^C_t}{\overline{Q}_t R^m_t}$. This "price-dividend" ratio of the cost claim solves a Bellman equation spelled out in Appendix B.

3.2.3 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). The market rent growth rate ε, the lease renewal rate s^O, the vacancy fill rate s^V, the net supply growth rate η, and the scaled costs c^{fix}, c^{var}, LC^N, and LC^R are all functions of the state z, inheriting its stochasticity.

Before 2020, the world was in a low-WFH regime, oscillating between the E and R states. The probability of a transition to either of the WFH states is zero.

The shift from the low-WFH world in 2019 to the high-WFH world in 2020 is an MIT shock. Once that shock has realized, the economy enters in the transition period, oscillating between the WFH-E and WFH-R states for as long as the transition regime lasts. The economy exits the transition and reaches the new steady state with probability $1 - p$ each period. The longer the transition lasts, the larger is the impact on office values. A key model ingredient is the uncertainty associated with the length of the transition, or equivalently, uncertainty about the size of the office value destruction.

The new steady state is a world with permanently higher WFH, but since demand and supply in the office market have fully adjusted to this new reality, it is characterized by the same parameters and state transition probabilities as the old pre-2020 steady state. Hence, the new steady state has the same valuation *ratios* $\widehat{V}_t^R$ and $\widehat{V}_t^C$ as the old steady state (but not the same office values).

We decompose the 4×4 state transition probability matrix as the Kronecker product of two 2×2 transition probabilities. The first matrix π^{BC} governs the dynamics between expansions and recessions. The second one π^{WFH} governs the length of the transition period. These two components are assumed to be independent:[12]

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

where

$$\pi_{WFH} = \begin{bmatrix} 1 & 0 \\ 1-p & p \end{bmatrix}.$$

With minor modifications, the model can accommodate permanent uncertainty about the state of WFH.[13]

3.2.4 State Prices

The one-period SDF takes the form $M(z'|z)$. We decompose this SDF into a component that governs the price of business cycle risk and a WFH shifter:

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

The benchmark model shuts down the WFH shifter by setting $M^{WFH}(z'|z)$ equal to a matrix of ones. The risk associated with the length of the transition is not priced.[14] In a robustness check, we allow for the uncertainty about the length of the transition (about the magnitude of the office value destruction), to be a priced source of risk in addition to the business cycle risk.

[12]The model can accommodate correlation between the components. However, such correlation is difficult to measure based on the short experience with the high-WFH state. There are opposing economic forces. On the one hand, a recession may result in more bargaining power for employers who may want employees to return to the office, shortening the transition. On the other hand, a recession may result in temporarily lower demand for office in an effort to cut costs, lengthening the transition period. Therefore, zero correlation seems like a natural compromise.

[13]Changing the first row of the state transition matrix to $[1-q, q]$ delivers a different model interpretation where the world oscillates between low- and high-WFH regimes. When q is small, that model's quantitative results for office values are similar as under the current interpretation.

[14]Intuitively, this means that the representative agent's marginal utility growth is independent of the state of the office market. This condition would be violated if, for example, a long transition resulting in a large office value destruction resulted in a decline in aggregate consumption, maybe by prompting a financial crisis.

3.3 Calibration

While risk and return vary across space, our initial focus is on NYC, 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 separate calibration for that segment of the office market. Section 4.3.1 conducts the calibration exercise for two more cities, San Francisco and Charlotte.

3.3.1 States and State Transition Probabilities

The model is calibrated at an annual frequency. 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 2×2 matrix $\pi^{BC}(z'|z)$:

$$\pi_{BC} = \begin{array}{c} \\ E \\ R \end{array} \!\! \begin{array}{c} \begin{array}{cc} E & R \end{array} \\ \begin{bmatrix} 0.879 & 0.121 \\ 0.563 & 0.437 \end{bmatrix} \end{array}.$$

The parameter p governs the expected length of the transition period once the economy has shifted to the high-WFH world. Since each period in the transition regime is associated with temporary but substantial cash flow declines, the higher p is, the larger the expected office value destruction. We will infer the value of p from the observed change in class A+ office valuations in 2020, as measured from office REIT data, and perform robustness with respect to this parameter. As explained below, this calibration delivers $p = 0.8750$.

3.3.2 State Prices

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:

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

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 in excess of inflation conditional on each pair (z, z'). We impose the conditional Euler equations for the aggregate stock market return Ret^{mkt} in 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 $M^{BC}(z'|z)$:

$$M^{BC} = \begin{array}{c} \\ E \\ R \end{array} \!\!\! \begin{array}{c} \begin{array}{cc} E & \quad R \end{array} \\ \begin{bmatrix} 0.757 & 2.776 \\ 0.322 & 1.791 \end{bmatrix} \end{array}.$$

The model matches the observed long-term average real risk-free rate of 0.5%. It implies a higher real risk-free rate in recessions than in expansions. The model also matches the historical average equity return of 11.1%. The equity risk premium is 10.5% unconditionally, and substantially higher in recessions (28.2%) than in expansions (6.7%).

3.3.3 Office Cash Flows for All NYC

Since we are interested in valuing the entire commercial office stock in New York City (All NYC), our main calibration is for the office stock of the entire city. The calibration is detailed in Appendix C.

We set the lease expiration parameter at $\chi = 0.14$. This delivers a lease duration of 7.27 years, matching the CompStak average office lease term in the NYC data. Table 1 lists the remaining parameters.

Market NER growth ϵ is calibrated to Compstak data. NER is strongly pro-cyclical. Market NER growth was -17.41% from December 2019 to December 2020 (one WFH-R year), and -2.12% per year from December 2020 to December 2023 (three WFH-E years). We notice substantially lower NER growth in the WFH-E (WFH-R) than in the E (R) state.

Net supply growth η, new construction minus depreciation and reductions in office space due to conversion to alternative use, is calculated from CompStak data. Supply growth is acyclical because of the long construction lags for office properties. Supply growth in WFH-R and WFH-E periods are calculated by down-scaling E and R supply growth by $\Delta\eta = 1\%$, consisting of a 0.5% point decline in office construction and a 0.5% increase in the rate of office conversion to alternative use.[15]

The parameters $s^O(E), s^O(R), s^V(E), s^V(R)$ govern office demand across the business cycle in the

[15] The amount of office conversion to alternative use was de minimis prior to 2020, with fewer than 0.1% of the office stock converted each year between 1993 and 2020. Office conversions accelerated in starting in 2021. JLL projects they reached 1% of the office stock in 2023. The average increase over the four years 2020–2023 is 0.5% points. Conversions from office to residential use are difficult for physical, regulatory, and financial reasons (Gupta, Martinez and Van Nieuwerburgh, 2023). The 0.5% point reduction in new construction is chosen to match the observed decline in office construction following the GFC.

Table 1: Calibration for All NYC

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0626	-0.1194	-0.0212	-0.1741
Supply growth	η	-0.0150	-0.0144	-0.0250	-0.0244
Lease renewal share	s^O	0.8504	0.3752	0.4499	0.1985
New leasing share	s^V	0.1788	0.3053	0.0946	0.1615
Fixed cost/rent ratio	c^{fix}	0.2000	0.2000	0.2000	0.2000
Variable cost/rent ratio	c^{var}	0.2300	0.2300	0.2300	0.2300
Leasing commission new	LC^N	0.3000	0.3000	0.2400	0.2400
Leasing commission renewals	LC^R	0.1500	0.1500	0.1200	0.1200

Notes: Market NER growth (ϵ) is calculated from CompStak data on net effective rents (NER) for NYC office leases from January 2000 to December 2023. Values for E and R states are based on pre-2020 data, WFH-R uses December 2019 to December 2020, and WFH-E values use December 2020 to December 2023. Supply growth (η) is computed using CompStak data on office building construction dates in NYC. The values represent new construction minus a 2.56% annual depreciation rate. This depreciation estimate corresponds to the 39 years of allowable depreciation expense for non-residential commercial real estate assets for tax purposes. WFH state values are adjusted downward by $\Delta\eta = 1\%$ to reflect reduced construction and increased conversion during the WFH transition. Lease renewal share (s^O) and new leasing share (s^V) are calibrated to match four moments of NYC contractual occupancy rate from Cushman & Wakefield data for 1987.Q1–2019.Q4. WFH state values are adjusted using a factor δ estimated from occupancy data for 2020.Q1–2023.Q4. Fixed (c^{fix}) and variable costs (c^{var}) are based on typical operating expense ratios for office properties, assumed to be constant across states. Leasing commissions for new leases (LC^N) and renewals (LC^R) are set based on industry standards of 30% commission on a 7-year 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.

pre-2020 era. We pin down these four parameters to match the mean, standard deviation, maximum, and minimum of the NYC contractual occupancy rate in Cushman & Wakefield data (Panel B of Figure 2). The resulting lease renewal share, s^O, is strongly pro-cyclical. The new leasing share for vacant space, s^V, is counter-cyclical, simply because there is much less vacant space available for lease-up in expansions. The parameters s^O and s^V in the transition states are assumed to be proportional to their pre-2020 counterparts:

$$s^i_{z,wfh} = \delta \cdot s^i_z, \qquad z = E, R, \quad i = O, V. \tag{2}$$

We estimate $\delta = 0.53$ to best fit the dynamics of the office occupancy rate over the 16 quarters from 2020.Q1–2023.Q4. The large downward shift in office demand in the transition period is consistent with the evidence documented in Figure A3.

Finally, the scaled fixed and variable costs as well as leasing commissions are assumed to be acyclical. This makes net operating income (revenue minus cost) more cyclical than revenues, generating operational leverage.

3.3.4 Office Cash Flows for A+ Properties in NYC

We use the CompStak leasing data 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.

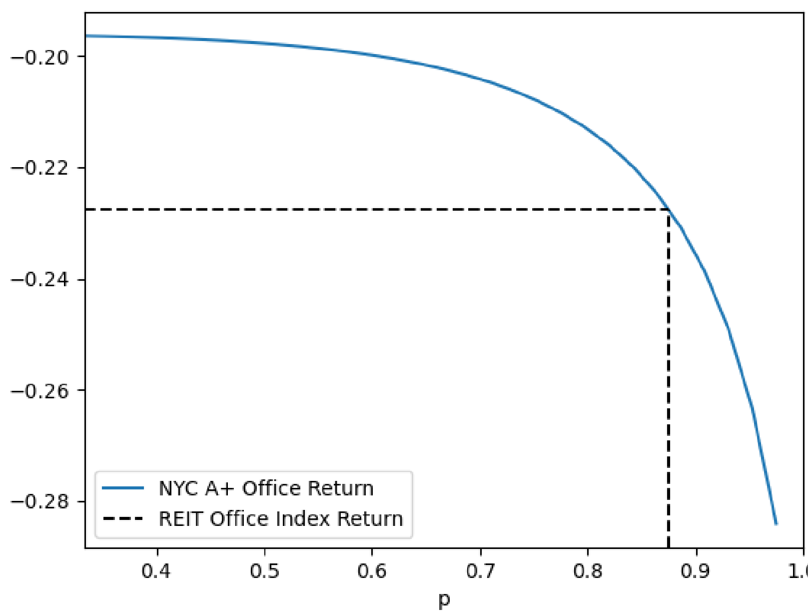
3.3.5 Identifying the Expected Length of the Transition Period

A key parameter in the calibration is p, which governs the length of the transition towards the new steady state once the economy has entered the high-WFH regime. Intuitively, the longer the transition lasts, the larger the decline in the valuation. We assume that the economy transitioned from the expansion state (the E state) in 2019 to the high-WFH recession state (WFH-R) in 2020. We compute the model-implied return on the NYC A+ office market in this transition, using the A+ calibration:

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

Figure 6 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 and monotonically with p, this moment is well-suited to identify this parameter.

Figure 6: Determining **p** by Matching Realized Return of A+ Market



Notes: This Figure illustrates our process for determining the persistence of the remote work state, p. We plot the model-implied realized return on A+ office real estate in the transition from an expansion state (E) in 2019 to a work-from-home recession (WFH-R) in 2020 for different values of the persistence parameter. This return depends also on $(\widehat{Q}^O_t, \widehat{R}^O_t)$ for 2019 and 2020, respectively. We obtain the values for these state variables by feeding in the sequence of annual aggregate shocks (E and R) from 1926 to 2019 obtained from the NBER recession chronology into the laws of motion of the states under the A+ calibration, delivering 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. We pick the parameter value which corresponds to the value drop realized by an index of office REITs between December 2019 and December 2020, after adjusting for leverage, as indicated by the dashed lines. Delevering is done based on leverage ratio and cost of debt data from NAREIT.

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 stock return of -36.16% between December 2019 and December 2020. After delevering this equity return, the asset return was -22.75%. The model matches this decline for a value of $p = 0.875$. 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 work.[16]

4 The Effect of WFH on Office Values

The model has realistic implications for unconditional and conditional moments, such as cap rates, expected returns and NOI growth rates, vacancy rates, and valuation ratios, discussed in Appendix D1.

4.1 Entire NYC 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 low-WFH state in 2019 to the WFH-R state in 2020.[17] The realized growth rate of potential gross rent in this transition is -19.42% in the model. The change in the scaled valuation ratio is -33.89%. Therefore, the overall value of the NYC office stock in this transition falls by 46.73%:

$$\left(\frac{\widehat{V}(\widehat{Q}^O_{20}, \widehat{R}^O_{20}, WFHR)}{\widehat{V}(\widehat{Q}^O_{19}, \widehat{R}^O_{19}, E)}\right)\left(\frac{\overline{Q}_{20}R^m_{20}}{\overline{Q}_{19}R^m_{19}}\right) = (1-33.89\%)\cdot(1-19.42\%) = (1-46.73\%).$$

Put differently, if the entire office stock of NYC had been marked-to-market, its value would have fallen by 46.73% over the course of 2020. The corresponding decline is only 27.25% for the A+ office sector, illustrating the relative safety of high-quality office.

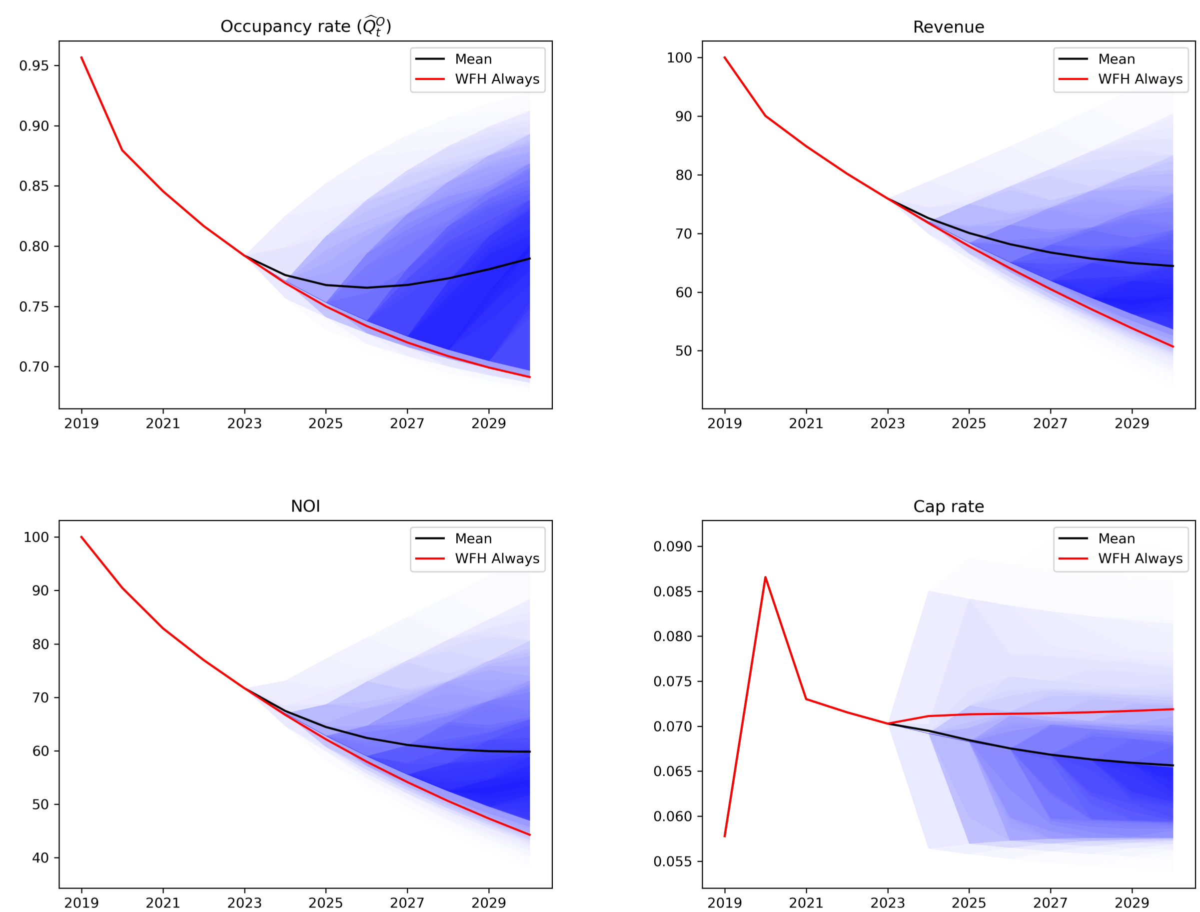
To understand the longer-run consequences of remote work, we conduct the following simulation exercise. In the first period of the transition, from 2019 to 2020, the economy goes from the E to the WFH-R state. In the second year, from 2020 to 2021, the economy transitions from WFH-R to WFH-E.

[16] 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– December 2023. This makes our results conservative. One could also use our procedure to update the implied persistence parameter over time.

[17] As we did for the A+ market, we feed in the observed history of expansions and recessions from 1926–2019 to arrive at the value for the endogenous state variables $(\widehat{Q}^O_{19}, \widehat{R}^O_{19})$ using the laws of motion for the states under the "All NYC" calibration. The model thus captures the decade-long expansion before 2020. We then apply the law of motion once more to obtain $(\widehat{Q}^O_{20}, \widehat{R}^O_{20})$ assuming the economy transitioned from E to WFH-R between 2019 and 2020.

In the third and fourth years (2022 and 2023), it stays in the WFH-E state. From 2024 onward, we let the economy evolve stochastically according to its laws of motion governed by π. Since there are many possible paths for the evolution of the state, Figures 7 and 8 show fan charts where darker blue colors indicate more likely future paths. The solid black line indicates the mean path. The red line plots the mean path conditional on the economy remaining in the transition regime every year until (at least) 2030. The probability of this event occurring is 39.28% according to the model.

Figure 7: Key Moments Distributions



Notes: The graph shows the evolution of key model moments for a transition from expansion in 2019 to WFH-R in 2020, WFH-E in 2021, 2022 and 2023. From 2024 onward, the state evolves stochastically. Revenue and NOI are normalized to 100 in Dec 2019. The shaded areas show percentiles of the distribution of simulated paths, with the darkest color indicating the 49–50 percentile range, and the lightest color the 1–98 percentile range.

The top left panel of Figure 7 shows the occupancy rate dynamics from the model simulation. The model captures a substantial decline in occupancy from a high value of 95.65% in 2019 to a value of 79.20% in 2023. In the data, there is a similar decline from 88.9% in 2019.Q4 to 77.2% in 2023.Q4. Since long-term leases continue to roll off and renew at low rates as long as the economy remains in transition, the decline in occupancy is protracted. Should the economy remain in transition until 2030, occupancy would eventually fall below 70% even after accounting for the supply response.[18]

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 ($Q^O R^O$) of 24.06% between 2019 and 2023, compared to the decline in active lease revenues in the data for New York City of 18.79% within the same period.[19]

Lease revenues go down 35.55% by 2030 along the average path. They fall by an additional 16% points for the red line, reflecting the larger vacancy rate, lower rents, and faster reduction in the quantity of office space if the economy remains in the high-WFH state for longer.

The bottom left panel shows that NOI falls by more than revenues since only variable costs decline in occupancy but not fixed costs. This is the operational leverage channel in action.

The bottom right panel shows that office cap rates were around 5.78% 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 6.18%.

The combination of declining cash flows and rising cap rates results in a substantial change in the value of office V_t, shown in Panel A of Figure 8. The graph illustrates a mean path that sees no recovery. Remote work is a near-permanent shock. More than a decade after the initial transition, office values remain at levels that are 46.47% below the valuation in 2019.

A second key message from our valuation exercise is that there is substantial uncertainty around the mean path. This uncertainty results from medium-frequency fluctuations between recession and expansion as well as from lower-frequency uncertainty about the length of WFH transition. Along some sample paths, the transition ends in 2024 or soon thereafter. Occupancy rates, rent revenues, and NOI recover.[20] These sample paths could be associated with faster return to office by existing firms, or new startup formation by firms which locate in central business districts, perhaps attracted by lower rental prices (Decker and Haltiwanger, 2023). Along other sample paths, the economy remains in the transition for a long period, and office values continue to fall. These trajectories can be associated with persistence and perhaps even heightened adoption of WFH practices, facilitated by new technological innovation which facilitate remote work (Bloom, Davis and Zhestkova, 2021). Conditioning on remaining in the

[18] Recall that supply growth in the transition is 1.0% points lower per year, capturing reduced construction as well as conversion of office to alternative use.

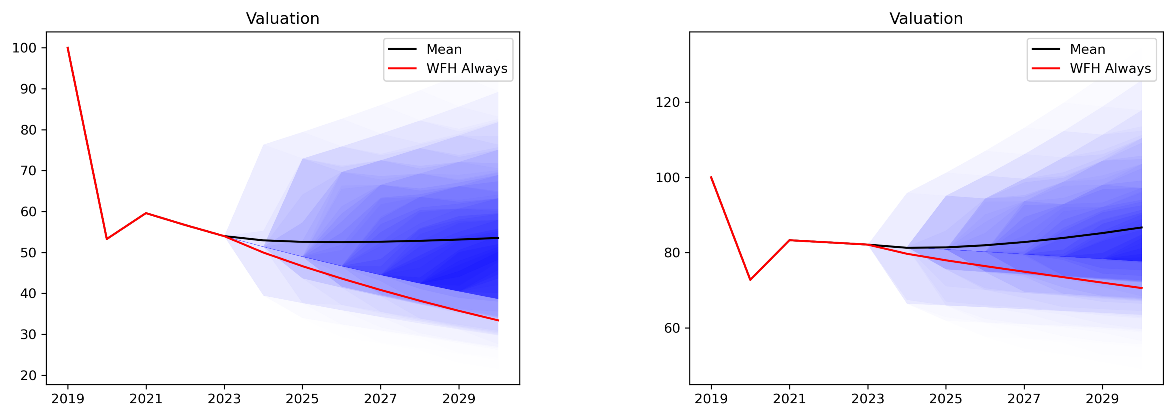
[19] To be consistent with our calibration method, we multiply the rent change in the CompStak data with the quantity change in the Cushman & Wakefield data to get the active revenue change.

[20] There is no full recovery since the first three years in the high-WFH state permanently reduce the size of the office stock.

Figure 8: Office Valuation Distribution

Panel A: All NYC

Panel B: NYC A+ Buildings



Notes: The graph shows the evolution of the office value V for a transition from expansion in 2019 to WFH-R in 2020, WFH-E in 2021, 2022 and 2023. Values are normalized to 100 in Dec 2019. From 2024 onward, the state evolves stochastically. The shaded areas show percentiles of the distribution of simulated paths, with the darkest color indicating the 49–50 percentile range, and the lightest color the 1–98 percentile range. Panel A shows the distribution of values for all NYC office buildings; Panel B focuses on A+ office value (buildings younger than five years or with a lease in the top ten percentile of the rent distribution in their submarket in the last five years).

transition state until at least 2030, average NYC office valuations are 66.60% lower in 2030 than in 2019.

Appendix D2 decomposes the overall effect of the WFH shock on office values into its components. The effect of rent growth dominates in the longer run while prices (NER) and quantities (occupancy and supply) adjust about equally in the short run.

4.2 A+ and the Flight To Quality

We perform a separate valuation exercise for the A+ segment of the NYC office market. Appendix D3 reports model output for cap rates, valuation ratios, and vacancy rates. The A+ segment features lower unconditional cap rates and lower expected returns, consistent with the lower risk of this segment. A+ properties also show more resilience in the transition period after the WFH shock, with lower vacancy rates, higher cash flow growth rates, and lower risk premia than for the NYC All calibration. Panel B of Figure 8 revisits the transition graph for office values. It shows substantially smaller value reductions both in the short- and long-run. The mean path has office values down by 13.33% in 2030 compared to 2019. In the scenario where the economy remains in the transition until at least 2030, the decline in A+ office values is 29.44%.

Conversely, the performance of the A-/B/C-class office segment is strictly worse than the overall market. Its initial value decline in 2020 is 63.97% compared to 46.73% for all office. Its long-run value decline is 75.79% compared to 46.47% for all office.

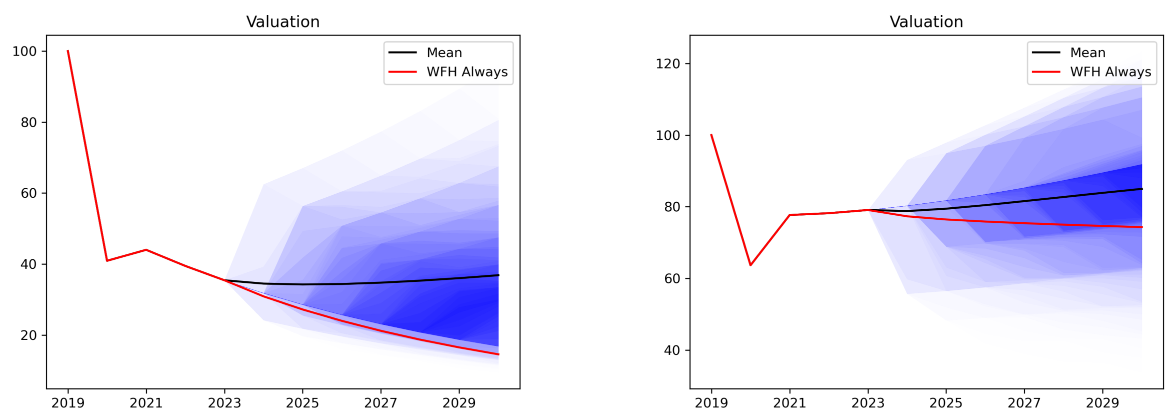
4.3 Other Office Markets and Aggregate Impact

4.3.1 San Francisco and Charlotte

We repeat the valuation exercise for San Francisco (SF) and Charlotte. Appendix D4 discusses the calibration and reports the resulting valuation moments. Figure 9 below shows the main fan chart for the valuation of the stock of SF office (left panel) and Charlotte office (right panel). The short-run (long-run) declines in office values along the mean path are 64.58% (63.15%) for SF and 20.90% (15.00%) for Charlotte. 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 consistent with SF's larger exposure to tenants from the technology sector who have more eagerly embraced remote work. Charlotte's valuation effects are smaller than NYC due to its milder office cycles and smaller exposure to the WFH shock.

Figure 9: Office Valuation Changes for Other Cities

Panel A: San Francisco | Panel B: Charlotte



Notes: The graph shows the evolution of the office value V for a transition from expansion in 2019 to WFH-R in 2020, WFH-E in 2021, 2022 and 2023. From 2024 onward, the state evolves stochastically. Office values are normalized to 100 in Dec 2019. The shaded areas show percentiles of the distribution of simulated paths, with the darkest color indicating the 49–50 percentile range, and the lightest color the 1–98 percentile range. Panel A shows results for San Francisco, and Panel B shows results for Charlotte.

4.3.2 Aggregate Impact

Table 2 compiles statistics on the top-20 U.S. office markets. Column 1 reports the quantity of active leases (in millions of square feet), Column 2 the percentage change in active lease revenue between December 2019 and December 2023, Column 3 the change in the quantity and Column 4 the change in the NER of newly-signed leases over the same period. These statistics show that the weakness in office fundamentals is widespread. NYC is not an outlier. The bottom panel compares the top-20 office markets to the remaining 85 Compstak office markets and shows similar changes in Columns 2–4.

Table 2: Cross-Sectional Results For Top 20 Markets

State	Market	(1) Active sf (mil)	(2) Lease Rev Chg (%)	(3) New sf Chg (%)	(4) NER Chg (%)	(5) Value Chg ($ Bil)	(6) Coverage (%)	(7) Value Chg Tot ($ Bil)	(8) Value Chg (%)
NY	New York	328.43	-13.99	-48.19	-9.40	-75.94	84.10	-90.30	-38.87
CA	San Francisco	76.29	-20.60	-69.47	-29.18	-23.70	77.40	-30.62	-54.14
NC	Charlotte	25.67	-7.40	-92.70	-33.20	-0.44	53.10	-0.83	-9.96
DC	Washington DC	112.31	-22.60	-42.47	1.54	-22.31	117.35	-19.01	-44.99
CA	Los Angeles	88.33	-22.11	-47.10	-13.12	-15.49	50.90	-30.43	-44.65
MA	Boston	81.31	-7.28	-66.98	-13.83	-13.10	51.74	-25.32	-34.11
IL	Chicago	116.95	-17.23	-64.93	-10.47	-10.07	59.92	-16.81	-41.17
WA	Seattle	48.27	-18.58	-92.27	-44.81	-6.19	82.19	-7.53	-42.14
GA	Atlanta	47.03	-12.99	-75.52	-7.50	-4.34	39.56	-10.97	-38.16
TX	Dallas	51.28	-18.98	-70.24	2.68	-5.09	28.69	-17.74	-42.42
CA	Orange County	44.58	-23.70	-48.27	-13.84	-5.27	54.88	-9.60	-45.78
CA	San Diego	35.84	-14.24	-83.07	-10.94	-4.58	50.54	-9.06	-39.05
TX	Houston	48.36	-33.62	6.56	-7.97	-5.87	32.87	-17.86	-52.83
VA	Arlington	31.56	-31.00	-53.86	20.98	-5.99	56.04	-10.69	-50.97
CA	Palo Alto & Sunnyvale	19.72	-4.56	-80.10	-16.90	-3.48	56.04	-6.21	-32.17
CA	San Jose	27.51	-21.36	-69.53	-19.97	-4.50	14.03	-32.07	-44.12
TX	Austin	35.17	-8.35	-67.47	-9.31	-3.08	72.10	-4.27	-34.87
CO	Denver	35.08	-20.33	-79.81	-17.09	-3.45	35.03	-9.85	-43.38
PA	Philadelphia	32.87	-14.70	-76.34	-44.49	-2.92	28.44	-10.27	-39.38
NJ	North Jersey	18.93	-16.42	-1.35	32.75	-2.32	20.83	-11.14	-40.60
Top 20 (Compstak)		1305.49	-16.74	-61.29	-18.20	-218.12	53.01	-370.57	-41.49
Other markets (Compstak)		1243.32	-16.07	-65.52	-15.05	-104.37	56.04	-186.24	-40.35
U.S. (Compstak)		2548.82	-16.52	-63.66	-16.87	-322.49	54.45	**-556.80**	-41.11

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 2022 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 December 2023. 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 2023. It combines the change in the value-to-revenue ratio over the first three 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 Charlotte 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 New York City calibration. The aggregate numbers in columns (4) for the top-20 markets, other markets, and national NER changes are adjusted by industry, building class, submarket, and renewal 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). The last column reports the percentage change in the value between the end of 2019 and the end of 2023.

Column 5 calculates the change in office values between December 2019 and December 2023. It combines the size of the market in Column 1, the change in revenues reported in Column 2, and the change in the value-to-revenue ratio from the model. For NYC, San Francisco, and Charlotte, we calibrated the model separately, delivering a value-to-revenue ratio change that is market-specific. The four-year value destruction is $75.9 billion for NYC, $23.7 billion for San Francisco, and $0.4 billion for Charlotte. For the other 17 large office markets, we use the market-specific size and revenue change in Columns 1 and 2 and combine them with the valuation-to-revenue ratio change for NYC to arrive at the value change in Column 5. Summed across the top-20 markets, we obtain a $218.1 billion value loss. Extending the analysis to the remaining 85 office markets, we find an additional $104.4 billion in value destruction for a total of $322.5 billion across all 105 markets in the CompStak data.

CompStak does not provide universal coverage. Based on Cushman & Wakefield reports, we are able to obtain a December 2019 coverage ratio estimate for 18 of the top-20 markets (Column 6). A coverage ratio of 56.0% for the remaining 87 markets (=105-18) reconciles the total U.S. office inventory in CompStak to that in Cushman & Wakefield. To obtain our total value impact statistic in Column 7, we divide Column 5 by Column 6. We arrive at an aggregate \$556.8 billion loss in office values nationwide over the 2019–2023 period. The largest dollar losses are in NYC (\$90.3 billion), San Jose (\$32.1 billion), San Francisco (\$30.6 billion), Los Angeles (\$30.4 billion) and Boston (\$25.3 billion). Relative to the end of 2019 valuation, the U.S. office stock lost 41% of value by the end of 2023, as indicated in Column 8.

4.4 Intensive Margin Variation in WFH

Work form home has become prevalent, but future changes in the number of days employees work from home are likely, as firms adjust their policies or as remote work technologies evolve. While the average number of days employees are allowed to work remotely is not a complete measure of WFH, it serves as one useful proxy which enables us to analyze the importance of changes in WFH intensity. We use the model to quantify the impact on office values from such intensive margin shifts in WFH.

To discipline this exercise, we estimate the cross-sectional relationship between city-level remote work, measured as the number of days employees are able to work remotely using the Scoop data, on the one hand, and city-level changes in office occupancy rates and average rents between 2019 and 2023. We allow the regression coefficients to depend on population density and report the coefficient estimates in Table A13 of Appendix Section D5. Cities which allow more hybrid work, in the form of more days worked remotely, experience higher office vacancies and larger drops in office rents. We use the estimated coefficients for the top-tercile of density—since we are primarily interested in understanding the effects for large population centers like NYC and San Francisco—to recalibrate model parameters (ϵ, η, s^o, s^v) for different WFH scenarios. Table A14 shows the resulting parameters.

We then simulate office valuations under the various WFH intensity scenarios, with results shown in Figure A15. An additional one-day increase (decrease) per week worked from home results in an office value decline between 2019 and 2030 that is 6.1% larger (6.9% smaller) than the decline in the baseline model. These results suggest that future changes to WFH policies could have a meaningful impact on office values.

4.5 Sensitivity Analysis

We conduct several robustness checks. First we explore sensitivity to the value of p, which governs the expected length of the transition. Figure A16 plots the NYC office value decline in 2020 for a range of values for p. For an expected transition period of 4 years ($p = 0.75$), the valuation decline is 39.90% (compared to 46.73% in the benchmark with an expected transition of 8 years).

Next, we study sensitivity to another important parameter: market NER growth in the WFH-R state. That parameter is hard to pin down since we have only observed one realization of that state. Figure A17 shows that setting NER growth in the WFH-R state equal to that in the R state, a natural alternative calibration, has only minimal effect on office values compared to the benchmark.

Our benchmark model assumes that uncertainty about the length of the transition, or equivalently about the magnitude of the office value destruction, is not a *priced* source of risk. Appendix D8 explores the possibility that the transition period could be associated with higher risk premia. Cash flows in these states are then discounted by an additional discount factor M^{WFH}. We consider a range of values for M^{WFH} that translate into an additional equity risk premium ranging from -1% to +5% per year. Figure A18 shows that the initial value decline is 45.30% when the risk premium is -1%, 46.73% when the risk premium is 0% (benchmark), 48.18% when the risk premium is 1%, and 52.95% when it is 5%. This shows that most of the valuation impact results from cash flow effects and priced business cycle risk, while the impact of priced transition risk is modest.

The transition to the WFH state affects office values through both cash flow and discount rate channels. To illustrate the role of priced business cycle risk, we conduct an exercise in Appendix D8 where we make the market price of cash flow shocks independent from the business cycle. That is, we set M^{BC} such that it takes on the same value for all four states z'. We match the same (observed) unconditional equity return in both expansions and recessions, rather than matching the different (observed) equity risk premium conditional on expansions and on recessions. Figure A19 shows that the office value decline is only modestly lower in the short-term (-41.90% vs. -46.73% in 2020 in the benchmark model). The higher discount rates during expansion in this alternative model lowers the effective duration of the office cash flows and hence lead to smaller decreases in valuation.

In Appendix D10, we disentangle the impact of the transition from the uncertainty about the length of the transition period. To do so, we calibrate an alternative model with a deterministic transition length. Figure A20 shows that the office value decline is modestly higher when the transition ends in $1/(1-p) = 8$ years for certain (-52.09% in 2020 vs. -46.47% in the benchmark model). The possibility of an early exit increases values more than the possibility of a late exit reduces it, increasing the valuation in the benchmark model. This occurs because of discounting and because vacancy growth decelerates as time passes during the WFH transition period.

Finally, Figure A21 performs four sensitivity analyses for San Francisco office values to (i) rent growth in the WFH-E state, (ii) the reduction in supply growth in the WFH states, (iii) the expected length of the transition period, and (iv) the introduction of a floor on office values as a simple way to model optionality arising from adaptive reuse (not already captured by the net supply parameter η).

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, notably working from home. We estimate a 46.7% decline in the value of New York City's office stock since the start of 2020. Since the transition to a new normal is likely to be protracted, the model expects office values in 2030 to remain 46.5% below pre-2020 levels. The numbers for NYC are not an outlier; we find similar effects across many of the largest U.S. office markets. Our novel valuation model is suitable for calibration to office markets in other locations, other commercial real estate sectors, and other real assets.

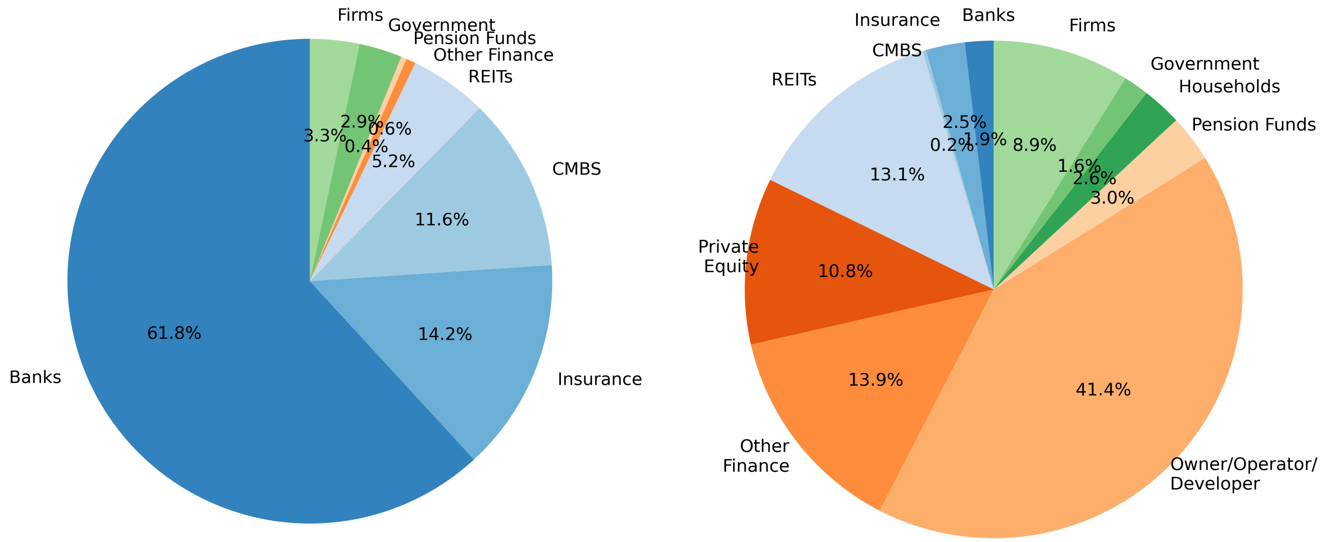
These valuation changes are large, but since about 80% of the office stock is privately-held and private transactions have been few (and represent a heavily selected sample), it has been difficult to directly observe the valuation changes. One exception is office REIT stocks, whose (unlevered) valuation declines are matched by our model both at year-end 2020 and 2023. Starting in 2023, an increasing number of distressed office transactions have begun to materialize at sale prices consistent with the model's predictions.

The predicted decrease in office values, particularly for lower-quality offices, impact both equity and debt holders under a standard capital structures.[21] As depicted in the right panel of Figure 10, equity ownership of office properties is widely spread among various investor types. Debt ownership, shown in the left panel, is more concentrated with banks holding over 60% of all CRE debt.

A large proportion of banks' assets is comprised of commercial real estate loans. This particularly true for medium-sized banks, for whom CRE loans represent about 25% of assets and who collectively hold about 70% of the bank CRE loans (see Figure A9 and Table A5). CRE loan exposure exceeds 300% of tier-1 equity capital for many small and mid-sized banks, a regulatory threshold in bank supervision. CRE credit risk compounds the negative impact of higher interest rates on bank equity, increasing the

[21] Before 2020, the typical office property was financed with around 65% debt (with little or no amortization) and 35% equity. A 65% asset value decline, the model's predicted decline for class A-/B/C offices, would result in a 100% loss in equity value and a 46% loss in debt value. Appendix A6 discusses evidence from debt markets consistent with declining office valuations.

Figure 10: CRE Debt and Equity Ownership



Panel A: Debt Ownership (All CRE, 2023) Panel B: Equity Ownership (Office, 2023)

Notes: Debt ownership data, used in the left panel, is from the Federal Reserve's Financial Accounts of the United States, Table L.220. It contains all commercial mortgages, excluding multifamily residential mortgage. Equity ownership data, used in the right panel, is from MSCI Real Capital Analytics as compiled from the history of transactions and valued at the RCA quality-adjusted market-specific CRE price indices for office by Koijen, Shah and Van Nieuwerburgh (2024). In the right panel, the category "Other Finance" combines the RCA investor categories Finance, Endowments, Investment Manager, Open-ended fund, Sovereign Wealth Funds. The category "REITS" combines the RCA investor categories REITS, REOCs, Non-traded REITS, and Listed Funds. The category "Households" combines the RCA investor categories High-Net-Worth and Non-profit User.

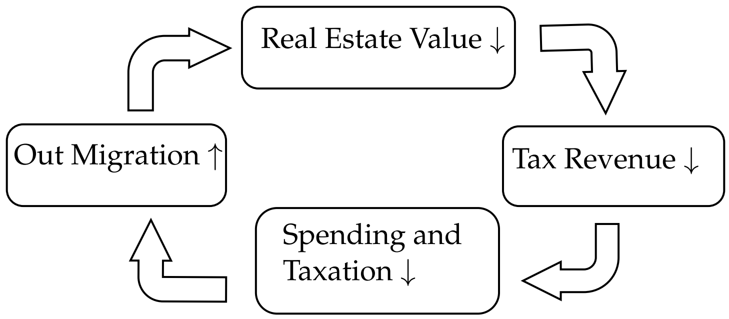
risk of financial fragility especially among regional banks (see also Jiang, Matvos, Piskorski and Seru, 2023, for recent work on this important topic).

Finally, the decline in office values and the surrounding urban retail properties, whose lease revenues have been hit as hard as office, have important implications for local public finances. Sales tax, real estate transaction tax, tourist hotel tax, parking meter, and personal and business income tax revenues took an immediate hit when many people escaped dense urban areas at the onset of the pandemic.[22] In the near future, downward pressure on commercial property tax revenue may create significant fiscal headwinds. Taxes from commercial property represent about 10% of tax revenue for the average city, with substantial variation across cities. They account for almost 36% of tax revenues in Boston, 26% in Dallas and 19% in Atlanta. NYC is close to the average with a 12.4% tax revenue share.[23] A 46.5% decline

[22]For example, San Francisco lost out on about $500 million in business tax revenue due to working from home. Business taxes represent 23% of overall tax revenue and San Francisco is heavily reliant on the largest firms. When these large firms let employees work from home, business tax revenues fell substantially since San Francisco uses a payroll apportionment factor which considers where employees are physically located. See `https://www.sf.gov/sites/default/files/2023-07/Business%20Tax%20LOI%20Response.pdf`.

[23]See `https://www.taxpolicycenter.org/taxvox/future-commercial-real-estate-and-big-city-budgets`. In NYC, $36.5 billion out of a total $112.4 billion (32.5%) in tax revenues comes from real property for the fiscal year that runs from July

Figure 11: Repercussions of Commercial Real Estate Valuation on Governments



in property values in NYC would, over time, result in a 4.2% reduction in tax revenues, assuming that effective tax rates are held constant.[24]

Given budget balance requirements, the fiscal hole left by declining commercial property tax revenues would need to be plugged by either raising other tax rates or cutting government spending on public safety, transit, sanitation, education, etc. Both choices reduce the attractiveness of the city for residence and work, and result in increased out-migration. These dynamics risk activating an "urban doom loop" (Figure 11) of lower tax revenues, reduced government services, and population loss. With more people being able to separate the location of work and home, the migration elasticity to local tax rates and amenities may now be larger than in the past. Future research should explore these implications and study the role for local and federal policy to mitigate the urban doom loop.

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 residential. 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 housing in large cities, but often runs into issues relating to structural feasibility, zoning restrictions, and return on investment (Gupta et al., 2023). Given the negative externalities associated with office vacancy, there is a role for local governments to facilitate conversions and speed up the transition towards a smaller office and larger housing stock. The extent of conversions will have an important impact on the vibrancy of neighborhoods and the future of cities.

1, 2024 until June 30, 2025. Commercial (tax class 4) property taxes are $14.0 billion or 12.44% of the total budget. An additional 3% of tax revenue comes from a tax on real estate tenants. Lower office and retail rents reduce that tax revenue.

[24] Most cities use a capitalization approach to assess commercial properties. The approach takes the net operating income and divides it by an administratively-set capitalization rate to obtain the assessed value. If the NOI declines by 46.5%, assessed values would decline by 46.5% as well. The decline would typically be phased in gradually over a number of years. An important question is whether tax authorities should additionally increase the administrative capitalization rate used in the assessment in recognition of the fact that the market capitalization rate has increased. This would further lower the property tax revenue. If the market capitalization rate increases from 4.5% to 9%, as it between 2019 and 2023, but the administrative capitalization rate is held constant at 9%, then the effective tax rate (tax payment as a share of market value) doubles, holding constant NOI, even when the statutory tax rate is unchanged. Owners have the right to appeal their property taxes and are increasingly doing so.

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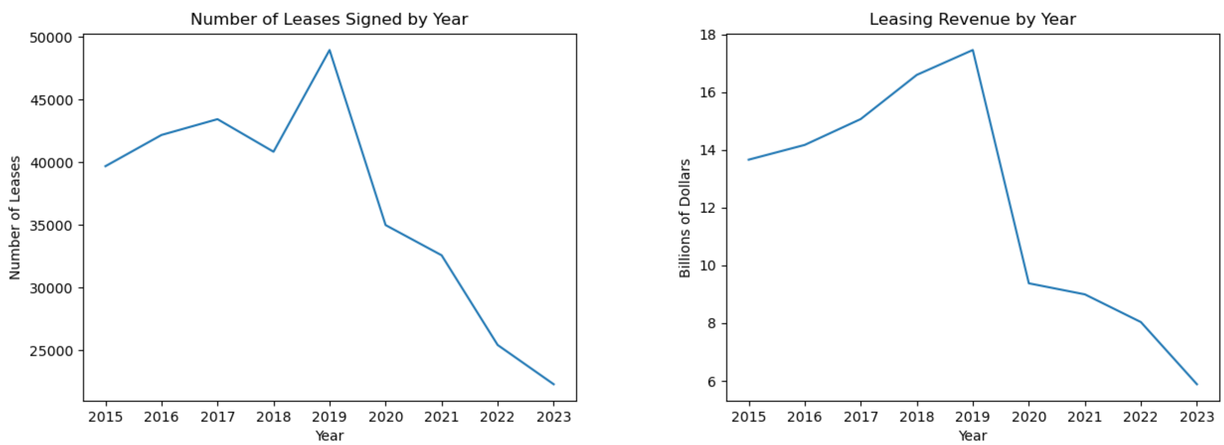
Online Appendix

A Additional Empirical Results

A1 Summary Statistics on Leasing

This section provides summary statistics for the CompStak data we use in this paper: We have 105 markets, 106,624 unique buildings, 623,030 leases, and 360,684 unique tenants in our entire sample. Figure A1 plots the number of newly signed leases per year between 2015 and2023 in the left panel, and the dollar value of those leases (in December 2022 dollars, right).

Figure A1: New Leasing Activities (2015-2023)



We compare the coverage of leasing in the CompStak data set to that with that of Cushman & Wakefield, one of the largest national office brokers, which publishes leasing aggregates by market. We find good coverage nationwide, but especially for our market of focus, New York City. As shown in Table 2 of the main text, our CompStak leasing database covers 84.1% of active leases in New York City at the end of 2019. Nationwide, we cover 54.5% of all active leases at the end of 2019.

At the national level, the *new leasing activity* in our CompStak data between Q1 2018 and Q1 2024 is 90.3% of the figure reported by Cushman & Wakefield.

Within Manhattan, Table A1 shows that the coverage ratio of our CompStak data relative to the Cushman & Wakefield data is high and stable over time (last column), with CompStak leases covering between 81% and 95% of Cushman & Wakefield leasing activity. CompStak has fewer new leases (column 1) and more renewal leases (column 2) than Cushman & Wakefield, but it is unclear how Extension and Expansion leases are categorized in Cushman & Wakefield data. In our CompStak data set, we include these under renewal leases.

Table A1: Manhattan Leasing Coverage Ratio

Year	New Leases	Renewal Leases	All Leases
2020	64.13%	125.36%	94.59%
2021	58.19%	170.73%	86.21%
2022	60.50%	164.87%	81.08%
2023	55.57%	130.29%	82.45%

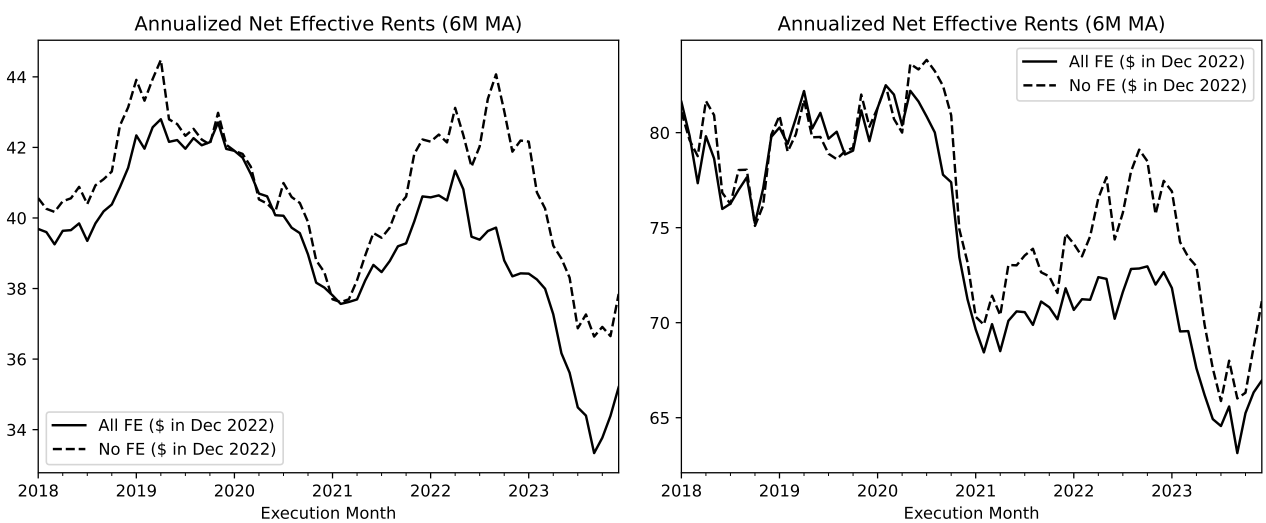
Notes: Our CompStak renewal activity measure includes the total square feet of Renewal, Expansion, and Extension leases. It is unclear whether Cushman & Wakefield includes the additional square feet that are part of Expansion leases and it is unclear whether they classify Extension as Renewals or as New Leases. Hence, a coverage ratio for renewal activities above 100% is possible.

A2 Evolution of Prices and Quantities of Newly-Signed Leases

New Lease Rents We study the dynamics of net effective rents (NER) on newly-signed leases. Figure A2 shows the square-foot weighted average NER on new leases, expressed in December 2022 dollars. Panel A shows results for the U.S. and Panel B subsets on NYC. Nationally, the NER fell by 8.59% in 2020. Starting in early 2021, the NER on newly-signed leases experienced a reversal with the NER ending up back at its pre-pandemic level at the end of our sample (dashed line). In NYC, the NER decline on new leases in 2020 is sharper at 8.89%, and the rebound in 2021 and 2022 is weaker.

Figure A2: Net Effective Rent on New Leases

Panel A: National　　　　Panel B: NYC



Notes: Panel A shows annualized net effective rents for all markets, while Panel B shows the NER for NYC. Dashed lines denote raw data while solid lines remove tenant industry, renewal, building class, state (panel A), major/non-major market (panel A), and submarket (panel B) fixed effects. Data are sourced from CompStak.

The national average NER dynamics may very well reflect composition effects, either in terms of the markets in which new leases are being signed or in terms of the types of tenants signing new leases.

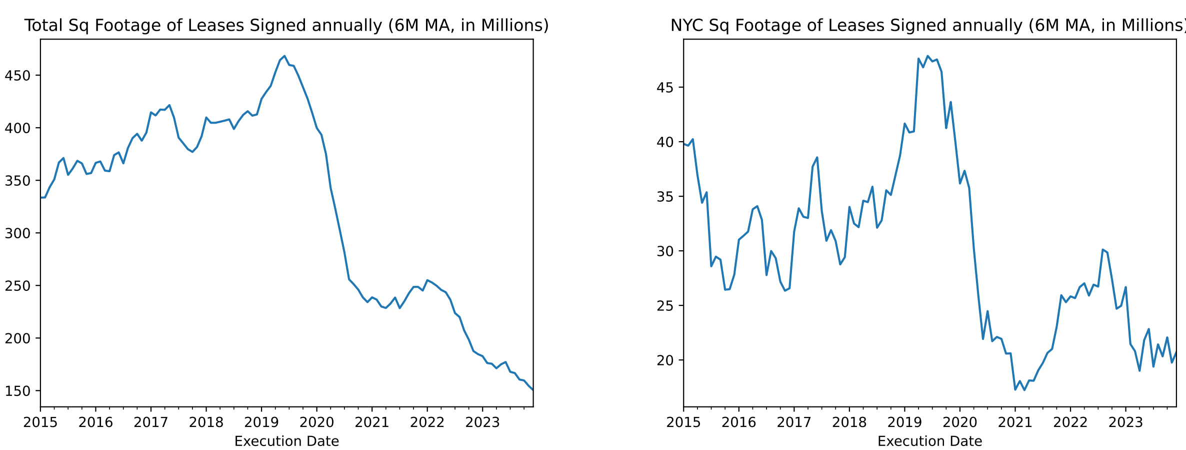
To partially control for such selection effects, we remove tenant-industry and geographical fixed effects. Once fixed effects are removed (solid line), both the decline in NER in 2020 and the rebound in 2021 become weaker. Much of the recent rebound in NER in the raw data turns out to be a spatial composition effect. We recall that this partial rebound happens amidst weak new leasing activity, and likely remaining selection on latent tenant or building quality. The measurement in NYC is less sensitive to the removal of tenant and submarket fixed effects. Again, the NER rebound weakens after fixed effects are removed.

New Lease Quantities Figure A3 investigates the effect of changes in office demand on the volume of new lease agreements. To do so, we aggregate the total number of new commercial office leases signed in the CompStak data. We observe a large decrease in the quantity of new leases signed, sometimes called absorption. Nationally (In NYC), the volume of newly signed leases fell from 414.09 (39.99) million square feet (sf) per year in the last six months of 2019 to 150.46 (20.72) million sf per year in the last six months of 2023. The graph suggests a large reduction in office demand from tenants who are actively making space decisions.

Figure A3: Quantity of New Leases Signed

Panel A: National

Panel B: NYC



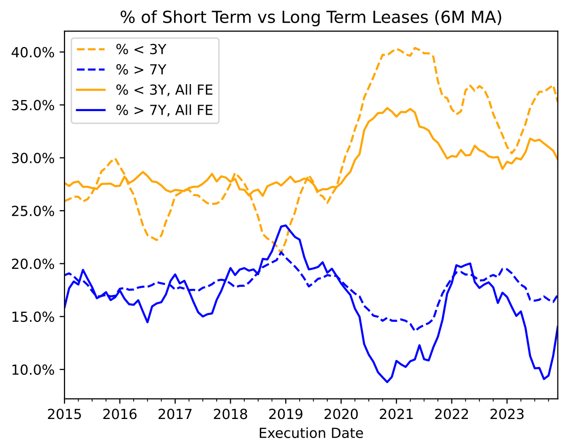
Notes: The graph shows the quantity of leases signed in square feet over time. Data are sourced from CompStak.

New Lease Durations Even when tenants do renew leases, they may not do so under the same set of terms. Panel A of Figure A4 shows that the share of new leases signed that are less than three years in duration increased substantially in 2020–21, while the share of leases with a duration more than seven years decreased.

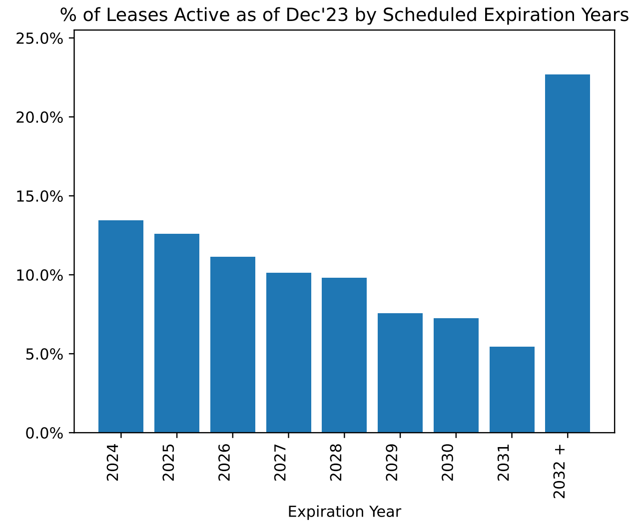
The shortening of lease duration suggests important shifts in the commercial office market, even conditional on lease renewal. As a result, the coming years 2024–2026 will feature even larger than expected lease expiration from two channels: the pre-scheduled expiration of long-term leases signed before the pandemic, as well as the expiration of short-term leases signed during the pandemic. The distribution of lease maturities as of the end of 2023 is shown in Panel B of Figure A4.

Figure A4: Lease Durations and Current Expiration Schedule

Panel A: Lease Duration Changes



Panel B: 2023 Expiration Schedule



Notes: Panel A shows the share of short-term (less than 3 year duration, in orange) and the share of long-term (more than 7 year duration, in blue) leases over time. Dashed lines denote raw data while the solid lines remove state, major/non-major market, industry, and renewal fixed effects. Panel B shows the percentage of leases expiring per year in square feet for leases that were in force as of December 2023. Data are sourced from CompStak.

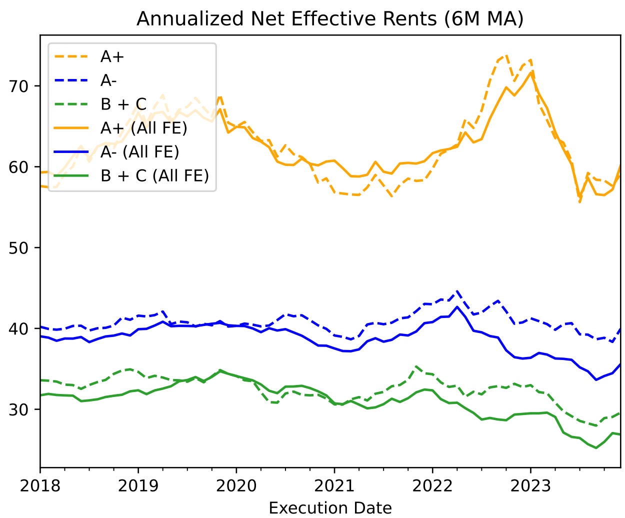
A3 Flight To Quality

We label the highest quality buildings as class A+ properties, defined based on rent levels and age. Specifically, we isolate leases that are either (1) in the top ten percent of the NER distribution in each quarter and submarket among all properties that are ranked as Class A by CompStak or (2) from buildings younger than five years. For the first "high rent" criteria, we categorize a building that has such a lease as A+ and assume that the A+ status remains for five years, unless another top-10% lease is signed in that building at which point the five-year clock resets. We pause new high-rent-criteria-based entry into the A+ group after December 2019 to avoid self-selection in the "flight-to-quality" effect. By this definition, 26.9% of square feet and 34.4% of lease revenue is in A+ office buildings in New York City. The remaining buildings ("others") are classes "A-" (A without A+), B, and C.

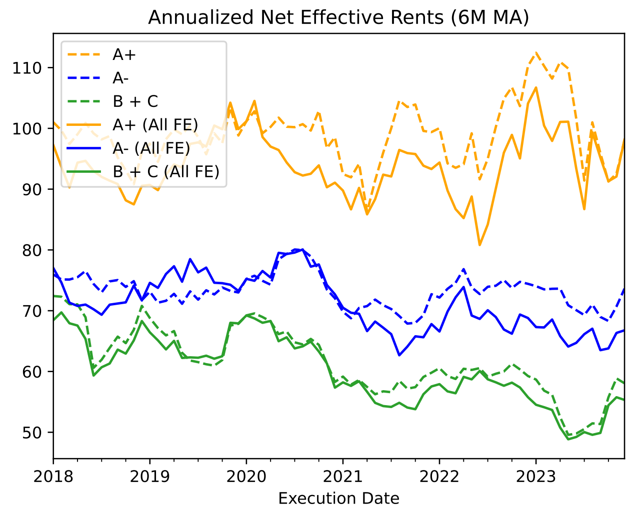
Figure A5 shows net effective rents (NER) on newly-signed leases grouped by building class. We focus on the solid lines, which remove fixed effects. Nationally, A+ rents on new leases show resilience, rising modestly between December 2019 and December 2022. Lower-quality office rents, by contrast, see a decline over this period. Similar patterns are present in NYC, shown in Panel B. Some of the A+ rent increase reverses in 2023 nationally, and to a lesser extent in NYC.

Figure A5: Net Effective Rent on New Leases By Building Class

Panel A: National



Panel B: NYC



Notes: The figure shows annualized net effective rents on newly-signed leases for all markets (Panel A) and NYC (Panel B). Rents are shown rents by building class: A+ (in orange), A- (in blue), B+C (in green). Dashed lines denote raw data while solid lines remove tenant industry, renewal, and state plus major/non-major market fixed effects (Panel A) and tenant industry, renewal, and submarket fixed effects (Panel B). Data are sourced from CompStak.

Figure A6 considers an alternative building quality measure based on building age. Younger buildings are defined as those younger than 10 years. Panel A displays changes in NER per square foot on *newly-signed* leases in NYC. Younger buildings hold on to their pre-2020 rent levels, compared to substantial rent decreases for other properties. This divergence suggests a "flight to quality" in office demand in these markets.

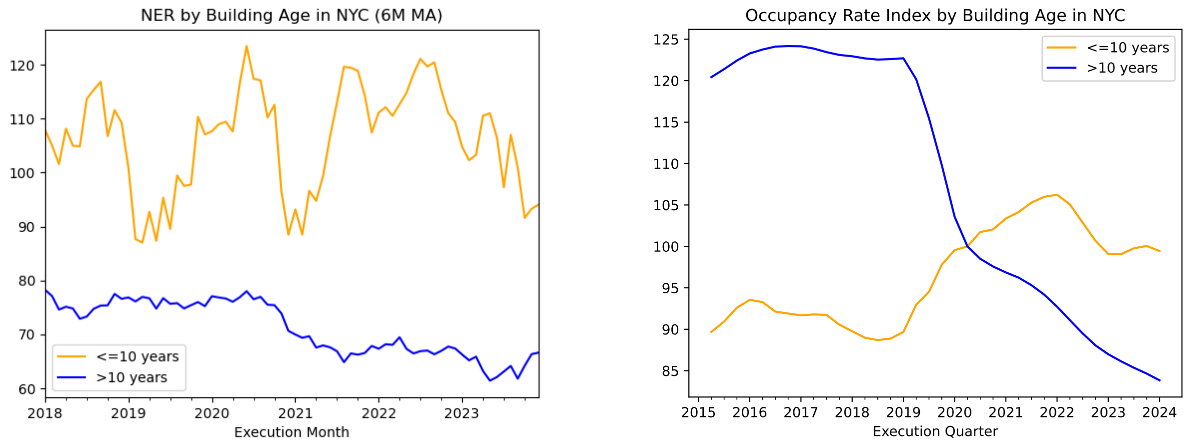
Panel B of Figure A6 shows changes in occupancy, which is the other main driver of revenue. The graph breaks out trends in occupancy across buildings of different ages. Occupancy rates are scaled relative to their December 2019 levels. The clearest expression of quality differentiation reveals itself in the strong occupancy levels of the young buildings, while the older buildings struggle to retain tenants.

Table A2 provides detailed regression results of the relationship between building age and NER. We control for month and submarket fixed effects (Column 1), and additionally for tenant fixed effects (Column 2). The specification in column 2 identifies the quality gradient from tenants that sign multiple leases, enabling a precise estimation of the association between age and rents. Each year of aging reduces

Figure A6: Flight to Quality Defined by Building Age

Panel A: NER in NYC

Panel B: Occupancy in NYC



Notes: Panel A shows the annualized NER in December 2022 dollars in NYC. The graph shows the split by building age (age less than 10 years in orange, all others in blue). Panel B shows occupancy rates in NYC by building age. Data are sourced from CompStak.

NERs by \$0.083 per sf in that specification. A building that is ten years older has 2.4% lower rents relative to the average rent of \$34.6 per sf.

Our key test for flight to quality is how this age changes after March 2020, represented as an interaction term with *Post* in column 3. This specification compares rent outcomes for leases signed in March 2020 and later, relative to leases signed between January 2018 and February 2020. We observe that the coefficient on the interaction of building age and *Post* is negative and significant, indicating that young buildings become even more valuable after the pandemic. The quality premium increases. Column 4 uses log NER and log building age, and shows an additional 3.9% point rent elasticity to age, a 47% increase over the elasticity in the earlier period. Columns 5 and 6 show that this association is stronger in major markets, and Column 7 shows that it is particularly large in NYC and San Francisco.

A4 Measures of Physical Office Attendance

We use three primary data sources to measure and track the effect of WFH adoption on office attendance: Kastle Systems' Workplace Barometer, Placer.ai's Office Busyness Index, and XYsense's Workplace Utilization Index. These sources have distinct methodologies and their own strengths and weaknesses in measuring physical employee attendance in offices.

Kastle Systems Kastle Systems provides the Kastle Back-to-Work Barometer, which has become a widely cited measure of office occupancy during and after the COVID-19 pandemic. The data are drawn

Table A2: Building Quality and Rent

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Building Age (Yrs)	-0.109***	-0.083***	-0.076***		-0.085***	-0.105***	-0.224***
	(0.016)	(0.015)	(0.013)		(0.015)	(0.028)	(0.054)
Building Age × Post Pandemic			-0.064***		-0.024**	-0.102***	-0.110***
			(0.012)		(0.010)	(0.015)	(0.026)
Log Building Age				-0.083***			
				(0.006)			
Log Building Age × Post Pandemic				-0.039***			
				(0.006)			
Age × Post × Major Market					-0.056***		
					(0.015)		
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Submarket FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tenant FE	No	Yes	No	No	No	No	No
Sample	Full	Full	Full	Full	Full	Major Market	SF+NYC
N	175,012	78,887	175,012	174,743	175,012	61,180	12,340

Notes: This table estimates the relationship between property quality, measured by age, and net effective rent (NER). The dependent variable is NER expressed in 2022 dollars, except in column (4) in which the dependent variable is log(NER). The right-hand side controls always include the month of lease commencement and submarket fixed effects. The additional control is a fixed effect for tenant identity (not available for all leases). The sample includes leases signed from 2018–2023 for all columns. Column (6) additionally subsets to major markets, which include NYC, Philadelphia, Boston, Houston, Dallas, Austin, Nashville, Chicago, Atlanta, Miami, Washington D.C., Denver, Los Angeles, and San Francisco. Column (7) additionally subsets to NYC and San Francisco. To illustrate the changing premium on quality, we introduce an interaction with an indicator variable *Post* which is one after March 2020. Standard errors, in parentheses, are double clustered at the month of lease commencement and submarket level. We keep submarkets with more than 100 leases to implement the double clustering. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

from proprietary access control software, with activity data from keycard, fob, and app usage across the buildings that Kastle secures. The Kastle data covers 2,600 buildings and 41,000 businesses across 47 states. In Manhattan, the data is drawn from 200 buildings and 70,000 cardholders. Kastle reports that nearly two-thirds of its sample comes from Class A commercial buildings, but it also includes a range of other buildings to reflect the city's entire office real estate market. This fraction is is similar to the composition of Class A buildings in our CompStak dataset, suggesting representativeness along this dimension.

Placer.ai Placer.ai data, used by the consultancy Avison Young to create the Office Busyness Index, is another commonly cited measure for office utilization. Placer.ai uses anonymized mobile phone location data to track visits to office buildings. While specific numbers are not publicly available, Placer.ai claims to have data on millions of devices across the United States. A benefit of this data source is that it can cover a wider range of office buildings, including those without electronic access systems. It can also capture people who enter buildings but are not employees (e.g., clients or contractors). However, the data collection is limited to individuals who have a phone with location services enabled which are accessible by Placer. Further, this measure may over-count office occupancy as it includes individuals who may be passing by buildings, stopping in the lobby, or visiting co-located retail establishments, rather than for office attendance specifically. It may double-count people with multiple mobile devices.

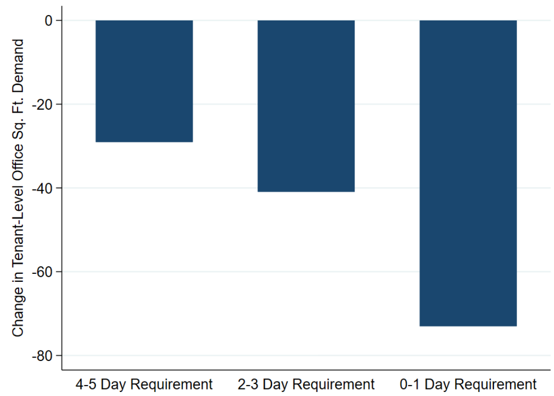
XYsense XYsense uses remote sensing technology to create a Workplace Utilization Index. These are based on sensors installed in office spaces to detect occupancy and movement patterns. Though specific coverage details are not publicly available, XYsense markets its solutions to a wide range of companies across various industries. The key advantage of this data source lies in providing highly granular data on space utilization within offices, not just building entry. However, it may have a smaller sample size compared to the other two methods, as it requires installation of proprietary sensors. The sample may be biased towards companies that are actively managing their office space utilization.

These three data sources typically show similar broad trends but can differ in both the current level of office occupancy and its recent evolution. For example, as of late 2023, Kastle data indicated office utilization at around 50% of pre-pandemic levels. Placer.ai data suggested a higher level of about 70%, partly due to recent increases. XYsense data agreed with Kastle on the 50% level at the end of 2023 but indicated a large jump in office utilization in the first quarter of 2024. These differences can be attributed to varying sample compositions, measurement approaches, and definitions of physical occupancy. In our analysis, we primarily reference the Kastle data due to its large sample size, direct measurement of building entry, and consistent tracking throughout the last five years.

A5 Relationship between office demand and remote work

Our baseline estimates of the relationship between firm office demand and WFH is based on an unweighted analysis on Scoop data. In Figure A7, we also consider a weighted analysis, which weights each firm by proportion of leases that were active in Dec 2019 and have come up for renewal by the end of 2023. We observe larger effects in this figure.

Figure A7: Firm Work Mode and Weighted Office Demand



Notes: This figure illustrates the relationship between firms' work-from-home (WFH) policies and changes in office space demand. The x-axis categorizes firms based on the number of days per week employees are expected to be in the office: 0-1 days (mostly remote), 2-3 days (hybrid), and 4-5 days (mostly in-office). This figure shows weighted results, where firms are weighted by the proportion of their leases that were active in December 2019 and came up for renewal by December 2023. Data on firm WFH policies are sourced from Scoop, and leasing data are from CompStak.

Table A3 provides the regression estimates corresponding to Figure 5. At the firm-level, each additional two days of remote work per week leads to a nearly 21 percentage point decline in office space (column 1). The remote work index is a three point scale, so a one unit increase corresponds to an increase in two days a week remotely for a firm going from 0–1 allowable remote days to 2–3, or from 2–3 days to 4–5 days a week.

We also observe this relationship at the industry and city levels, with each additional two days of remote work leading to a reduction in space demand by 15 percentage points at the industry level (column 2) and 7 percentage points at the city-level (column 3). Each additional two days of remote work will also lead to a reduction of 7 percentage points in average rent at the city-level (column 4).

As an alternative measure of firms' remote working plans, we also use job posting data from Ladders. This data allows us to measure the fraction of a firm's job listings that are for fully-remote positions. The Ladders data contains a flag indicating whether the position is remote or not. The platform focuses on job positions paying in excess of $100,000 a year, and so has high coverage of many remote working positions for knowledge workers.

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. We merge job postings and tenant data for 135 large tenants. Table A4 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

Table A3: Remote Work and Office Space Demand/Rent

	OLS (1)	OLS (2)	OLS (3)	OLS (4)
Remote Work Index (Firm)	-21.18			
	(15.87)			
Remote Work Index (Industry)		-14.56***		
		(3.64)		
Remote Work Index (City)			-6.90	-6.71
			(5.28)	(6.07)
N	559	14	63	91
Industry FE	Yes	No	No	No
City FE	Yes	No	No	No

Notes: This table shows the relationship between remote work plans and change in office space demand/office rent at different levels of aggregation. In column (1) and (2), we measure change in office demand by comparing firm's total leased square footage in December 2023 against the amount leased in December 2019. Our remote work index collapses plans into three levels (4–5 days a week in person, 2–3 days a week, and 0–1 days a week). A one unit increase therefore corresponds to allowing two additional remote days a week. Column (1) shows the relationship at the firm level. Column (2) shows the relationship at the industry-level, collapsing average remote work plans and change in office demand to the industry-level. Column (3) measures the relationship between remote work plans aggregated to the city level against city-level change in vacancy in Cushman & Wakefield. Column (4) measures the relationship between city-level remote work plans and city-level average rent change from 2019 to 2023 in CompStak. We remove the tenant industry, renewal, and submarket fixed effects from the deflated net effective rent, and then weight by transaction sq. ft. to calculate the average rent. Column (1) weights observations based on office space demand of each firm, while columns (2) – (4) weight observations based on the employment share of each industry and city, respectively. Standard errors in column (1) are clustered at the city-level.

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.

Table A4: Remote Listings and Office Demand

	(1) Δ Space	(2) Δ Space	(3) Δ Space
Remote Listings (3 months)	-0.392**		
	(-2.41)		
Remote Listings (12 months)		-0.492**	
		(-2.46)	
Remote Listings (24 months)			-0.468**
			(-2.01)
Constant	-0.0123	-0.0106	-0.0156
	(-0.61)	(-0.52)	(-0.77)
Observations	135	135	135
R^2	0.042	0.044	0.030

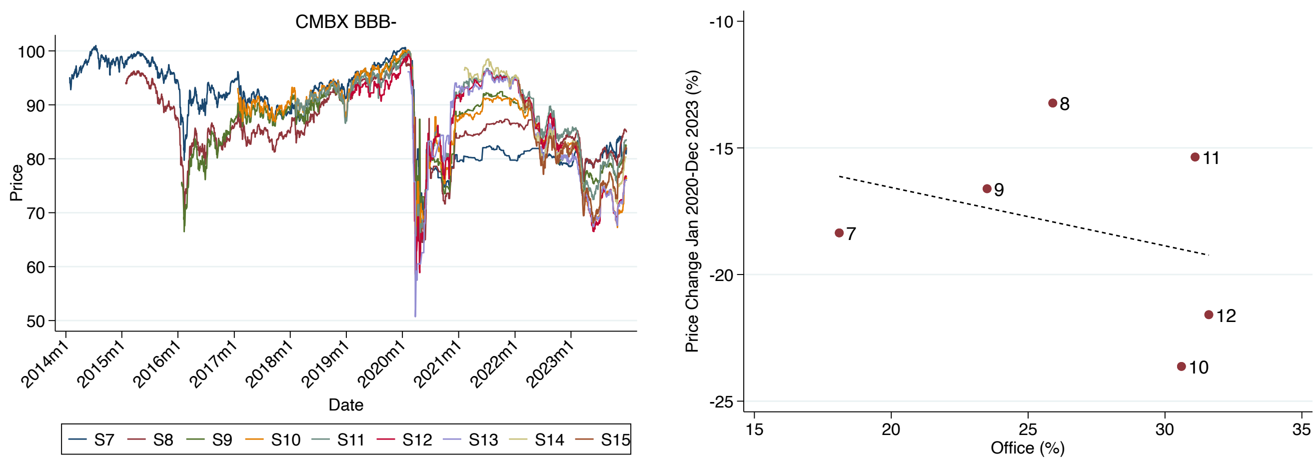
t statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable, Δ 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.

A6 Evidence from Public Debt Markets

Declining office valuations could be substantial enough to inflict losses on debtholders. Evidence from public debt markets is directionally consistent with this possibility. Figure A8 plots the time series of prices of CMBX tranches with credit rating BBB- of different vintages. Every six months, a new vintage of CMBX tranches is issued, indicated by a sequential number (we plot series S7–S15). Each BBB- CMBX tranche represents a pool of 25 BBB- tranches of the 25 largest CMBS deals issued in that six-month period. The collateral pool of each CMBS deal consists of a mix of office, retail, industrial, apartment, and hotel properties. The share of the collateral that consists of office-backed mortgages varies across the pre-2020 vintages (S7–S12). It is higher for series S10–12 than for series S7–9. Panel B shows that the price decline between the beginning of 2020 and the end of 2023 is larger for CMBX bonds with more office exposure.

Figure A8: Price of CMBX Insurance and Office Exposure



Panel A: CMBX Prices

Panel B: Office Exposure

Notes: Panel A shows prices for the Markit CMBX index of credit default insurance for BBB- tranches. 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. The different lines are for different vintages, denoted S7 through S15. Panel B plots the share of mortgages in each vintage that is backed by office properties in 2020 against the price change of the CBMX BBB- tranche between January 2020 and December 2023.

Extracting precise conclusions from the evolution of CMBX prices for the underlying values of office properties is very difficult for at least four reasons. First, CMBX tranches are portfolios of 25 CMBS bonds, each of which is a derivative on its own unique combination of typically around 50-100 commercial mortgages backed by a range of collateral assets. Each of these commercial mortgages has its own default risk, which depends on the features of that mortgage. But the likelihood of default of the BBB- tranche depends on the joint default probability and loss-given-default distribution of all loans in the pool. Hence, there is a complex relationship between a loss in asset value for the offices that collateralize the CMBS loans and the losses on the CMBX BBB- tranche. One could try to study prices of Single Asset Single Borrower (SASB) deals that have one or more office assets as collateral, but the market for SASB tranches is substantially less liquid.

Second, bond prices reflect beliefs under the risk-neutral, not the physical measure, and risk premia are time-varying. The years 2022 and 2023 were a risk-off period in the office debt markets, with little new issuance of office debt, except against the highest quality properties. This makes it difficult to ascertain the bond market's forward-looking view on the office sector over the next ten years, especially for average and below-average quality buildings.

Third, CRE bond prices depend on long-term Treasury interest rates, who have shown their own complex dynamics over the recent past: very low until the end of 2021, then a steep increase from the start of 2022 until late 2023, followed by a modest decline, with high volatility throughout. Most of the CMBX price increase at the end of 2023 is likely due to declining long-term Treasury rates rather than improvements in credit risk.

Fourth, distress in the bond market is a lagging indicator of office fundamentals, as lenders (and special servicers) postpone the recognition of losses (extend and pretend). CMBS bonds must price in the likelihood of success of these extension tactics.

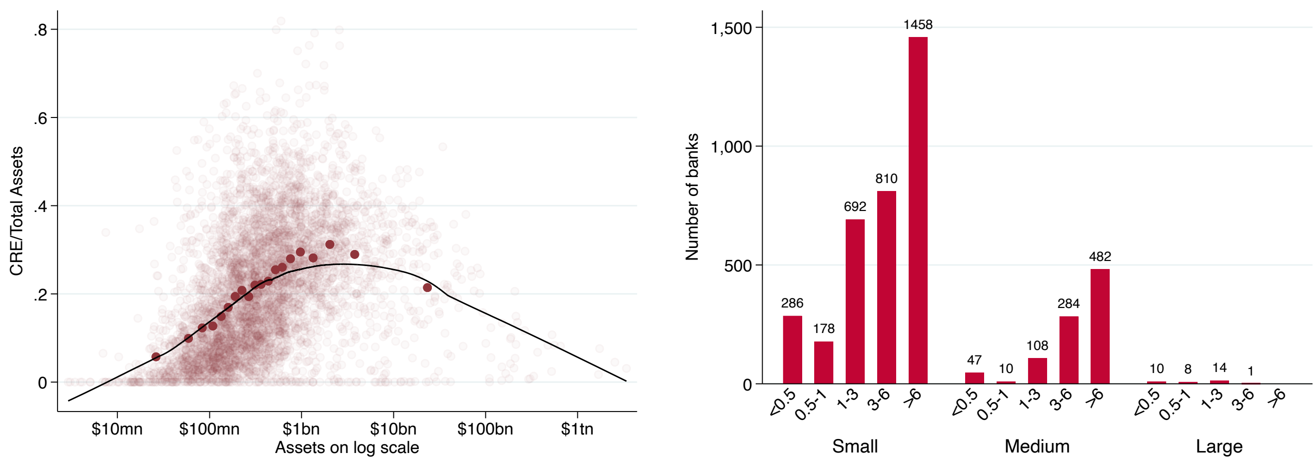
A7 Financial Fragility: Banks' CRE Exposure

In this section, we explore some of the implications of CRE debt exposure for banks, who bear much of the debt exposure.

We measure bank size by bank assets and banks' commercial real estate (CRE) exposure by their outstanding commercial real estate loans, using Call Report data at the end of 2023.Q4. We measure CRE loans using the variable "UBPRD489," which is the sum of (i) construction and land development loans, (ii) nonfarm nonresidential mortgages, (iii) unsecured loans to finance commercial real estate, construction and land development, (iv) other real estate owned, and (v) investments in unconsolidated subsidiaries and associated companies. We use the variable "UBPRP742" to measure common equity tier 1 capital, which is the sum of common stock and related surplus, net of treasury stock and unearned employee stock ownership plan (ESOP) shares.

Panel A of Figure A9 shows CRE loan exposure as a share of bank assets (vertical axis), plotted against log bank assets (horizontal axis) as of 2023.Q4. Each dot represents one bank. CRE exposure is inverse-U shaped in bank size, with the largest concentration of CRE risk in banks with around $1 billion in assets. Panel B shows the number of banks with different ratios of CRE loans to common equity tier 1 capital ($<$ 50%, %50 $-$ 100%, 100% $-$ 300%, 300% $-$ 600%, $>$ 600%) for small, medium, and large banks. Among small and mid-sized banks, a large fraction has CRE exposure that exceeds the supervisory threshold of 300% of tier-1 capital in CRE loans. Several hundred mid-size banks have a ratio that exceeds 600%. None of the large banks have this much exposure to CRE credit risk.

Figure A9: Commercial Real Estate Exposure By Bank Size



Panel A: CRE/Total Assets Panel B: CRE/Common Equity Tier 1 Capital

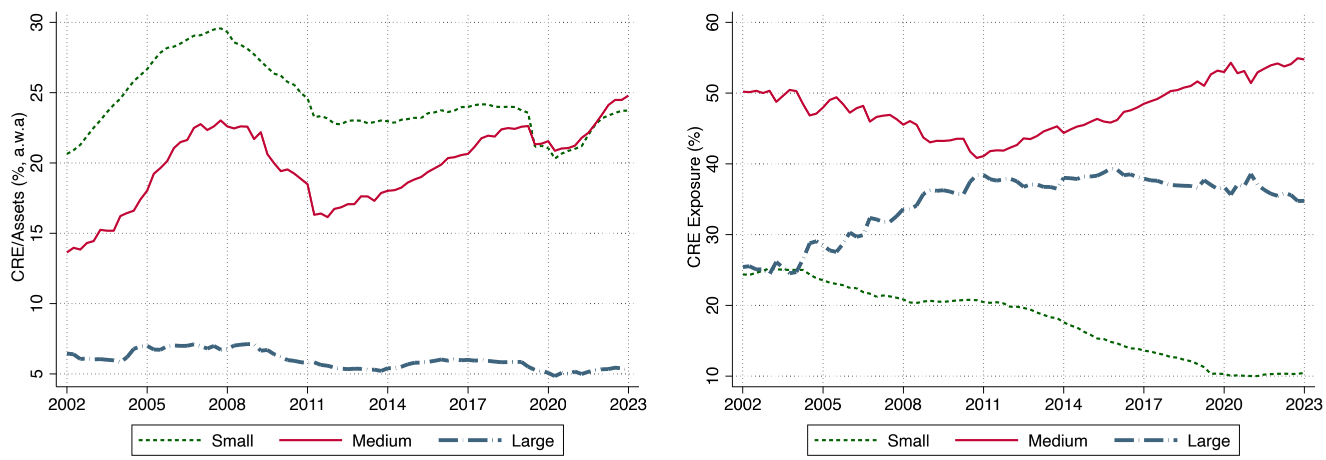
Notes: Panel A shows the ratio of commercial real estate loans to bank assets plotted against the log of bank assets for U.S. banks as of 2023.Q4. Panel B shows the number of banks as of 2023.Q4 within different categories of commercial real estate loans to common equity tier 1 capital ($<$ 50%, %50 $-$ 100%, 100% $-$ 300%, 300% $-$ 600%, $>$ 600%) for small ($ $<$ 1 billion in assets), medium ($1 $-$ $100 billion), and large ($ $>$ 100 billion) sized banks. Data are from the 2023.Q4 Bank Call Reports.

Table A5 reports various categories of bank size (Column 1), the number of banks in each group (Column 2), the fraction of aggregate bank assets the group represents (Column 3), the asset-weighted average ratio of CRE loans to bank assets (Column 4), and the fraction of total CRE loans held by banks in that group (Column 5). We find that medium and small banks are most exposed to CRE risks, with average exposures of around 20-28% of assets, while the largest banks with over $250 billion assets have only moderate CRE exposure ($<$ 5%). Nonetheless, the dollar value of their CRE exposure still accounts for 25.2% of all CRE loans. About 70% of banks' CRE exposure and about 40% of overall CRE exposure sits on the balance sheet of regional and smaller banks.

Table A5: Commercial Real Estate Exposure by Bank Size

(1) Bank Size ($ bi)	(2) Count	(3) Asset Share (%)	(4) CRE/Asset (%, awa)	(5) Exposure Share (%)
>250	14	57.6	4.8	25.2
100–250	19	13.4	7.8	9.5
50–100	13	3.8	22.8	7.9
25–50	35	5.2	20.9	10.0
10–25	77	5.2	24.2	11.5
1–10	836	9.9	27.9	25.4
0.25–1	1,758	3.8	25.6	8.9
<0.25	1,889	1.0	16.6	1.5

Figure A10: Commercial Real Estate Exposure of Banks over time



Panel A: CRE/Total Assets

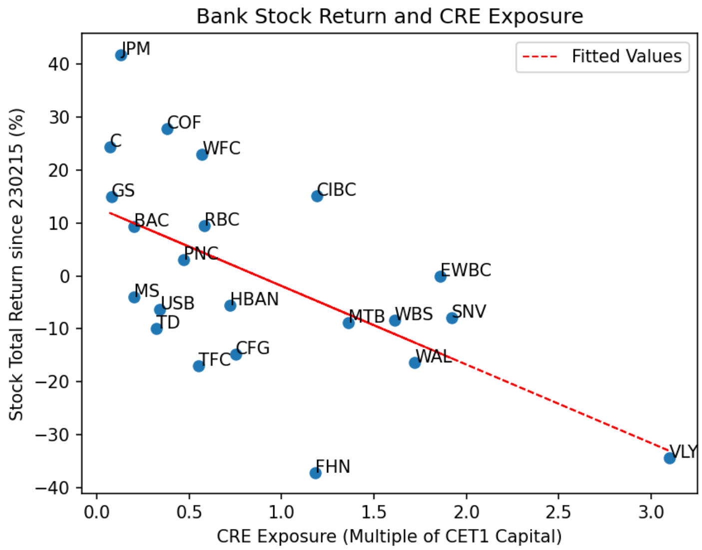
Panel B: CRE Exposure (%)

Notes: Panel A shows commercial real estate loans as a proportion of total assets by bank size over time. We show three different bank sizes: Small ($ $<$ 1 billion in assets), Medium ($1 $-$ $100 billion), and Large ($ $>$ 100 billion). Banks are divided into these groups in each quarter using assets expressed in 2023.Q4 dollars. Within each category, we plot the asset-weighted average. Panel B shows the share of overall CRE loans held by each group over time. Data are sourced from the Call Reports.

Panel A of Figure A10 shows CRE loans as a proportion of total assets over time for three size groups. CRE exposure (CRE debt relative to bank assets) has increased for medium-sized banks, while it has decreased for larger banks. Panel B shows the evolution of the composition of CRE debt. The share of bank-held CRE debt that is held by the medium-sized banks has increased substantially since 2011.

Next, we consider the implications of CRE holdings on bank equity exposure, for publicly listed banks. We focus on the period around the collapse of Silicon Valley Bank (SVB), at which point the markets began to price in commercial real estate exposure. Figure A11 below shows that the stocks of banks with large CRE exposure in late 2022 indeed experienced much lower stock returns over the ensuing period. These results highlight the broader spillovers of commercial real estate exposure on other intermediaries.

Figure A11: Bank Stock Return and CRE Exposure



Notes: The figure shows the cumulative stock return between Feb 15, 2023 and Apr 4, 2024 and the CRE exposure of the top U.S. banks. The data source of stock return is Bloomberg, and the data source of CRE Exposure is S&P Capital IQ . CRE exposure is defined by CRE loans as of 3Q'22 excluding owner-occupied, construction and land development, farm, and multi-family loans.

B Model Derivation

This section contains the full derivation of the model in Section 3. The goal is to solve the following equation:

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

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

B1 Revenue

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

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

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

$$\frac{\bar{Q}_{t+1}}{\bar{Q}_t} - 1 = \eta_{t+1}(z') \quad \Rightarrow \quad \bar{Q}_{t+1} = \bar{Q}_t(1 + \eta_{t+1}(z'))$$

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

$$\hat{Q}_t^O = \frac{Q_t^O}{\bar{Q}_t} \quad \Rightarrow \quad Q_t^O = \hat{Q}_t^O \bar{Q}_t.$$

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 $\bar{Q}_{t+1}$ and Q_t^O,

$$\hat{Q}_{t+1}^O \bar{Q}_t(1+\eta_{t+1}(z')) = min\{\hat{Q}_t^O \bar{Q}_t(1-\chi) + \hat{Q}_t^O \bar{Q}_t \chi s_{t+1}^O(z') + (\bar{Q}_t - \hat{Q}_t^O \bar{Q}_t)s_{t+1}^V(z'), \bar{Q}_t(1+\eta_{t+1}(z'))\}$$

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

Next, the rent revenue in the building/market in period $t+1$ is,

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

To derive the law of motion for R_t^O, we rewrite Rev_{t+1} as,

$$Q_{t+1}^O R_{t+1}^O = Q_t^O(1-\chi)R_t^O + \Big[Q_t^O \chi s_{t+1}^O(z')R_{t+1}^m + (\overline{Q}_t - Q_t^O)s_{t+1}^V(z')R_{t+1}^m\Big]$$

Dividing by Q_{t+1}^O we get,

$$R_{t+1}^O = \frac{Q_t^O}{Q_{t+1}^O}(1-\chi)R_t^O + \Big[\frac{Q_t^O}{Q_{t+1}^O}\chi s_{t+1}^O(z')R_{t+1}^m + \Big(\frac{\overline{Q}_t}{Q_t^O}-1\Big)\frac{Q_t^O}{Q_{t+1}^O}s_{t+1}^V(z')R_{t+1}^m\Big]$$

which is the law of motion of R_t^O.

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

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

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 $\hat{R}_{t+1}^O$:

$$\begin{aligned}
\widehat{R}_{t+1}^O &= \frac{Q_t^O}{Q_{t+1}^O}(1-\chi)\frac{R_t^O}{R_{t+1}^m}\frac{R_t^m}{R_t^m}\frac{\overline{Q}_{t+1}}{\overline{Q}_{t+1}}\frac{\overline{Q}_t}{\overline{Q}_t} + \Big[\chi s_{t+1}^O(z')\frac{Q_t^O}{\overline{Q}_t}\frac{\overline{Q}_t}{\overline{Q}_{t+1}}\frac{\overline{Q}_{t+1}}{Q_{t+1}^O} + s_{t+1}^V(z')\frac{Q_t^O}{\overline{Q}_t}\frac{\overline{Q}_t}{\overline{Q}_{t+1}}\frac{\overline{Q}_{t+1}}{Q_{t+1}^O}\Big(\frac{1-\widehat{Q}_t^O}{\widehat{Q}_t^O}\Big)\Big] \\
\widehat{R}_{t+1}^O(\widehat{R}_t^O,\widehat{Q}_t^O,\widehat{Q}_{t+1}^O,z') &= \frac{(1-\chi)\widehat{R}_t^O}{(1+\epsilon_{t+1}(z'))(1+\eta_{t+1}(z'))}\frac{\widehat{Q}_t^O}{\widehat{Q}_{t+1}^O} + \Big[\frac{\chi s_{t+1}^O(z')}{(1+\eta_{t+1}(z'))}\frac{\widehat{Q}_t^O}{\widehat{Q}_{t+1}^O} + \frac{s_{t+1}^V(z')(1-\widehat{Q}_t^O)}{(1+\eta_{t+1}(z'))\widehat{Q}_{t+1}^O}\Big].
\end{aligned}$$

We define scaled revenues as

$$\widehat{Rev}_{t+1}(\hat{Q}_t^O,\hat{R}_t^O,z') = \frac{Rev_{t+1}}{\bar{Q}_t R_t^m}.$$

Rewriting the equation for $Rev_{t+1}(Q_t^O,R_t^O,z')$:

$$\begin{aligned}
Rev_{t+1}(\hat{Q}_t^O,\hat{R}_t^O,z') &= \hat{Q}_t^O\bar{Q}_t(1-\chi)\hat{R}_t^O R_t^m + \Big[\hat{Q}_t^O\bar{Q}_t\chi s_{t+1}^O(z') + (\bar{Q}_t - \hat{Q}_t^O\bar{Q}_t)s_{t+1}^V(z')\Big]R_t^m(1+\epsilon_{t+1}(z')) \\
Rev_{t+1}(\hat{Q}_t^O,\hat{R}_t^O,z') &= \bar{Q}_t R_t^m\Big[\hat{Q}_t^O(1-\chi)\hat{R}_t^O + \Big[\hat{Q}_t^O\chi s_{t+1}^O(z') + (1-\hat{Q}_t^O)s_{t+1}^V(z')\Big](1+\epsilon_{t+1}(z'))\Big].
\end{aligned}$$

Scaled Revenue $\widehat{Rev}_{t+1}$ can be written as

$$\widehat{Rev}_{t+1}(\hat{Q}_t^O, \hat{R}_t^O, z') = \hat{Q}_t^O(1-\chi)\hat{R}_t^O + \Big[\hat{Q}_t^O \chi s_{t+1}^O(z') + (1-\hat{Q}_t^O)s_{t+1}^V(z')\Big](1+\epsilon_{t+1}(z')).$$

The expected present discounted value (PDV) of revenues is written as

$$V_t^R = E_t\Big[\sum_{j=1}^{\infty} M_{t,t+j} Rev_{t+j}\Big].$$

The scaled version of revenues can be written as:

$$\hat{V}_t^R = \frac{V_t^R}{\overline{Q}_t R_t^m},$$

which solves the following Bellman equation:

$$\hat{V}_t^R(\hat{Q}_t^O, \hat{R}_t^O, z) = \sum_{z'} \pi(z'|z) M(z'|z) \Big[\widehat{Rev}_{t+1}(\hat{Q}_t^O, \hat{R}_t^O, z') + (1+\eta(z'))(1+\epsilon(z'))\hat{V}_{t+1}^R(\hat{Q}_{t+1}^O, \hat{R}_{t+1}^O, z')\Big].$$

Finally, we get V_t^R by

$$V_t^R = \hat{V}_t^R(\hat{Q}_t^O, \hat{R}_t^O, z)\overline{Q}_t R_t^m.$$

B2 Costs

The building costs are written as:

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

Substituting for R_{t+1}^m, we get,

$$\begin{aligned} Cost_{t+1} = {} & C_{t+1}^{var}(z')Q_{t+1}^O + C_{t+1}^{fix}(z')\overline{Q}_{t+1} + \\ & \Big[\hat{Q}_t^O \bar{Q}_t \chi s_{t+1}^O(z') LC_{t+1}^R(z') + (\bar{Q}_t - \hat{Q}_t^O \bar{Q}_t)s_{t+1}^V(z') LC_{t+1}^N(z')\Big] R_t^m (1+\epsilon_{t+1}(z')). \end{aligned}$$

We define scaled costs as:

$$\widehat{Cost}_{t+1} = \frac{Cost_{t+1}}{\bar{Q}_t R_t^m}.$$

Therefore, we have:

$$\widehat{Cost}_{t+1} = \frac{Cost_{t+1}}{\overline{Q}_t R_t^m}$$
$$= c_{t+1}^{var}(z')\widehat{Rev}_{t+1} + \left[c_{t+1}^{fix}(z')\widehat{R}_{t+1}^O(1+\eta(z')) + \hat{Q}_t^O \chi s_{t+1}^O(z') LC_{t+1}^R(z') + (1-\hat{Q}_t^O) s_{t+1}^V(z') LC_{t+1}^N(z')\right](1+\epsilon(z'))$$

where

$$c_{t+1}^{fix}(z') = \frac{C_{t+1}^{fix}(z')}{R_{t+1}^O} \qquad c_{t+1}^{var}(z') = \frac{C_{t+1}^{var}(z')}{R_{t+1}^O}.$$

The expected PDV of costs is written as:

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

The scaled version is:

$$\hat{V}_t^C = \frac{V_t^C}{\overline{Q}_t R_t^m},$$

which solves the Bellman equation

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

Finally, we get V_t^C by

$$V_t^C = \hat{V}_t^C(\hat{Q}_t^O, \hat{R}_t^O, z)\overline{Q}_t R_t^m.$$

C Calibration Algorithm

The following describes the steps in the calibration algorithm for the universe of NYC office buildings (NYC All) and the subset of A+ buildings (NYC A+). We set the depreciation to 2.56% in both calibrations, equal to the depreciation rate of commercial properties for tax purposes of 39 years. 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.

C1 NYC All, 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 χ equal to the reciprocal.
3. Estimate ε from data:
   (a) To estimate $\varepsilon(E)$ and $\varepsilon(R)$, first calculate NER series for each month controlling for submarket, tenant industry, leasing type, and building class FEs, 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 rolling window falls in recession, then that rolling year is considered to be a recession; otherwise it is considered to be an expansion. We use the leasing cycle definition instead of the business cycle.
   (c) Compute the annual growth rate of the six-month moving average rent, and take the average separately for expansions and recessions.
   (d) Estimate $\epsilon(WFHR)$ as the annualized realized NER growth between March 2020 and December 2020, and $\epsilon(WFHE)$ as the annualized realized rent growth between December 2020 and December 2023.
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. We look at growth after 1950 for NYC All.

(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 separately for expansions and recessions.

(d) Finally, we subtract the rate of depreciation to arrive at $\eta(E)$ and $\eta(R)$.

5. Set $\eta(WFHE) = \eta(E) + \Delta\eta$ and $\eta(WFHR) = \eta(R) + \Delta\eta$. We choose $\Delta\eta = 1\%$ to capture two forces that drive the supply side response post the WFH shock: (1) The excess office supply resulting from remote and hybrid work would create a transitory reduction in supply growth. We calibrate this impact by matching the average supply growth reduction in NYC, following another large demand reduction in office, namely the Great Financial Crisis. The supply growth from 2010 to 2019 in NYC was -0.5% below the long-term average in the regular expansion state. (2) Additionally, some of the office stock will be converted to other usages and reduce the total supply. We calibrate the conversion rate to be 0.5% annually based on the realized conversion in the past four years. CBRE reports that in 2023.Q4 the planned/underway office conversion ratio in the U.S. is around 2%. Within those conversion projects, a small number of them may have started before the pandemic. However, we also expect an acceleration of office conversion in the coming years, given the sluggish nature of supply responses. Therefore, we choose to average the 2% across four years, or 0.5% per year, to obtain the annual office conversion rate. We provide sensitivity analysis on the choice of $\Delta\eta$ in Section D11.[25]

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 2019.Q4:

   (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 δ relative to their no-WFH counterparts: $s^{\{V,O\}}(WFH) = \delta \cdot s^{\{V,O\}}(no - WFH)$. Estimate the parameter δ to best fit the dynamics of the office occupancy rate in the 16 quarters from 2020.Q1–2023.Q4. The first 4 quarters are WFH-R and the last 12 are WFH-E. The

[25] Source: https://www.cbre.com/insights/briefs/more-office-conversions-underway-to-revitalize-downtowns.

dynamics are given by the model:

$$\hat{Q}^O_{t+1}(\hat{Q}^O_t, z') = \frac{s^V_{t+1}(z')}{1+\eta_{t+1}(z')} + \hat{Q}^O_t \cdot \frac{1-\chi+\chi s^O_{t+1}(z') - s^V_{t+1}(z')}{1+\eta_{t+1}(z')}.$$

C2 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 NYC All, with the following modifications:

4. When calculating η for A+ buildings, we collect all the buildings that have ever entered into the A+ universe, given our time-varying definition of A+ buildings, and re-do the calculation for NYC All. Since A+ is only a subset of NYC market, we start the calculation of *eta* for each year from 1970 to 2019 to avoid extreme value caused by lack in coverage.

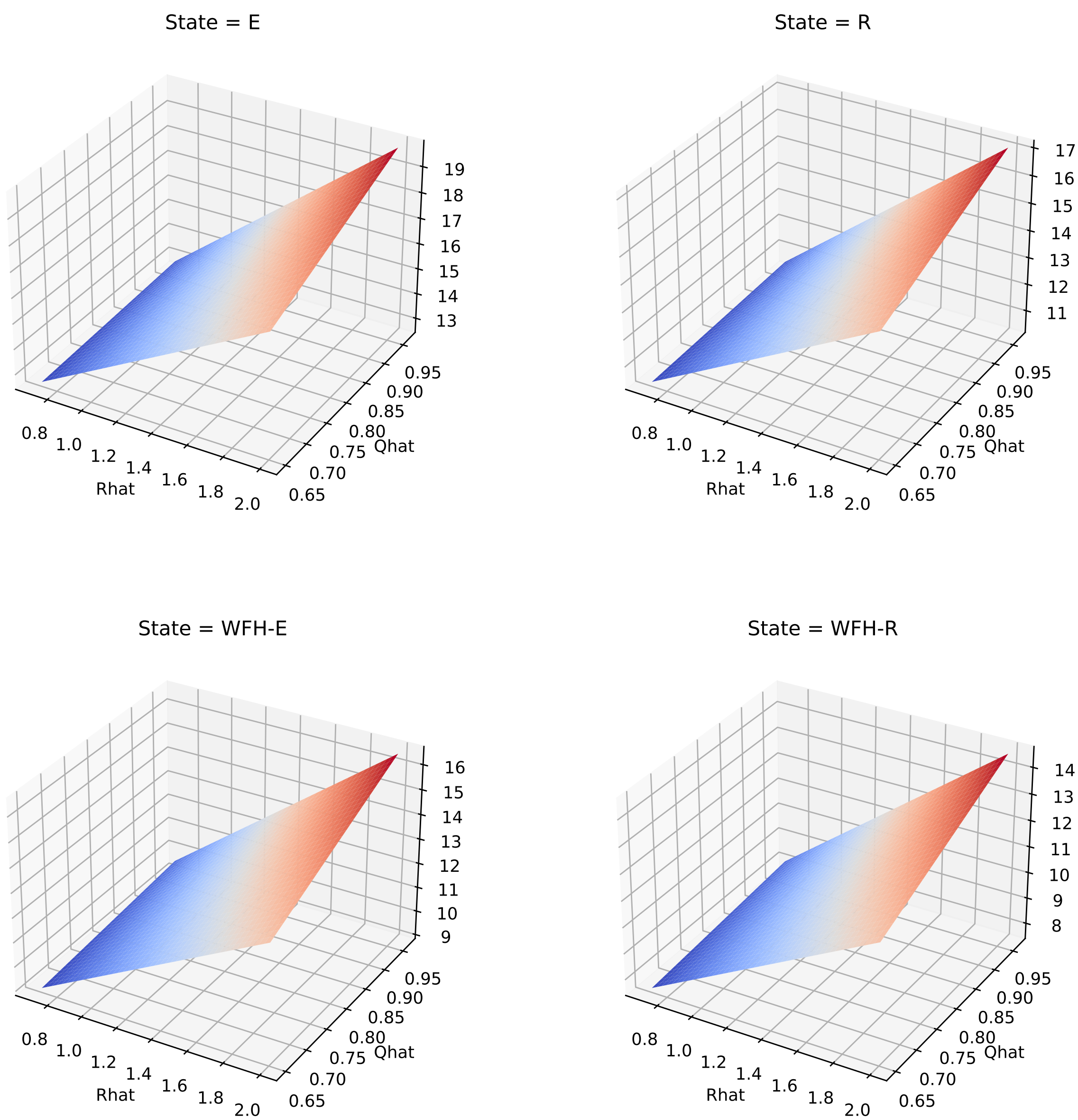
5. The NYC A+ calibration takes $\Delta\eta$ from the NYC All calibration.

6. We use data from NAREIT on the U.S. office sector occupancy from 2000.Q1 to 2019.Q4 to calibrate $\{s^O(E), s^O(R), s^V(E), s^V(R)\}$. We target a minimum occupancy rate that's lower than the empirical min in this sample period, because the A+ occupancy data is missing in the 1990s, which is the worst historical period for office occupancy. We assume that both A+ and the entire Manhattan office market experienced the same number of standard deviation decline from their mean since 2000 when they reached their own minimum in the 1990s.

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 3.3.5.

Figure A12 shows the valuation ratio for office $\widehat{V}$ conditional on expansion, recession, WFH-expansion and WFH-recession for the All NYC calibration. The x-axis plots the grid for $\widehat{Q}^O$ and the y-axis shows the grid for $\widehat{R}^O$. Office valuation ratios are increasing in both occupancy $\widehat{Q}^O$ and rent $\widehat{R}^O$.

Figure A12: $\hat{V}$ for All NYC Market by States



Notes: This Figure shows the valuation ratio $\hat{V}$ for the entire New York City office market under four different economic states: Expansion (E), Recession (R), Work-From-Home Expansion (WFH-E), and Work-From-Home Recession (WFH-R). The valuation ratio is plotted as a function of two state variables: the occupancy rate $\widehat{Q}^O$ (x-axis) and the rent ratio $\widehat{R}^O$ (y-axis).

D Model Results

D1 Model Outcomes for the NYC All Market

Table A6 presents key unconditional and conditional moments for the benchmark "NYC All" office calibration. The model delivers a reasonable unconditional average cap rate of 6.18% for the overall NYC office market. The cap rate is 7.32% in recessions and 5.93% in expansions.[26]

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 look at the two components of the cap rate. The model implies an expected return on NYC office of 8.17% and an office risk premium of 7.63%. This is naturally lower than the equity risk premium of 10.54% since an unlevered office property is less risky that the aggregate stock market (which is a levered investment). The office risk premium is substantially higher in recessions (12.88%) than in expansions (6.47%). Expected NOI growth is 1.33% unconditionally. This number is in real terms and incorporates that the office stock depreciates, so that real NOI growth is 3.89% before depreciation (=1.33%+2.56%). Expected cash flow growth is higher in expansions than in recessions. While the likelihood of transitioning from a recession to an expansion state is reasonably high, the NOI growth rate conditional on staying in the recession state is very negative while the NOI growth conditional on leaving the recession state is only mildly positive.

Vacancy rates are 7.6% on average, higher in recessions than expansions by 6.56% points, and much higher conditional on being (and remaining) in the remote work transition, around 25.1%.

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 6.87 times potential gross rent unconditionally according to our calibration. The average valuation ratio of office properties in the E state of 7.01 is 33.62% higher than the value of 5.25 in the WFH-R state.

[26] The hedonic-adjusted cap rate for Manhattan Office averaged 5.3% over the period 2001–19 according to Real Capital Analytics data. The model predicts a 6.02% average cap rate for the same period. The discrepancy is mostly explained by the unusually low interest rates in the 2001–19 period. Longer data from CBRE put the average office cap rate for NYC at 7-8%, close to our model's steady-state. Like the model, the Real Capital Analytics data indicates higher cap rates in recessions than in expansions.

Table A6: Model Solution for NYC All Calibration

Statistic	Uncond	E	R	WFHE	WFHR
R_f	0.0054	-0.0012	0.0372	-0.0012	0.0372
Equity $\mathbb{E}[Ret]-1$	0.1108	0.0660	0.3192	0.0660	0.3192
Equity RP = $\mathbb{E}[Ret]-1-R_f$	0.1054	0.0672	0.2820	0.0672	0.2820
Cap rate	0.0618	0.0593	0.0732	0.0720	0.0896
Office $\mathbb{E}[Ret]-1$	0.0817	0.0636	0.1660	0.0491	0.1322
Office RP = $\mathbb{E}[Ret]-1-R_f$	0.0763	0.0647	0.1288	0.0503	0.0950
$\mathbb{E}[g_t]$	0.0133	0.0219	-0.0268	-0.0602	-0.0789
Vacancy rate $=1-\widehat{Q}^O$	0.0762	0.0646	0.1302	0.2470	0.2681
$\widehat{\text{Rev}}$	0.8034	0.8084	0.7801	0.8427	0.8629
$\widehat{\text{Cost}}$	0.3796	0.3809	0.3734	0.4338	0.4485
$\widehat{\text{NOI}}=\widehat{\text{Rev}}-\widehat{\text{Cost}}$	0.4238	0.4275	0.4067	0.4089	0.4145
$\widehat{V}^R$	13.2311	13.4948	12.0048	11.1585	10.5973
$\widehat{V}^C$	6.3610	6.4810	5.8031	5.6081	5.3481
$\widehat{V}=\widehat{V}^R-\widehat{V}^C$	6.8701	7.0138	6.2017	5.5503	5.2492

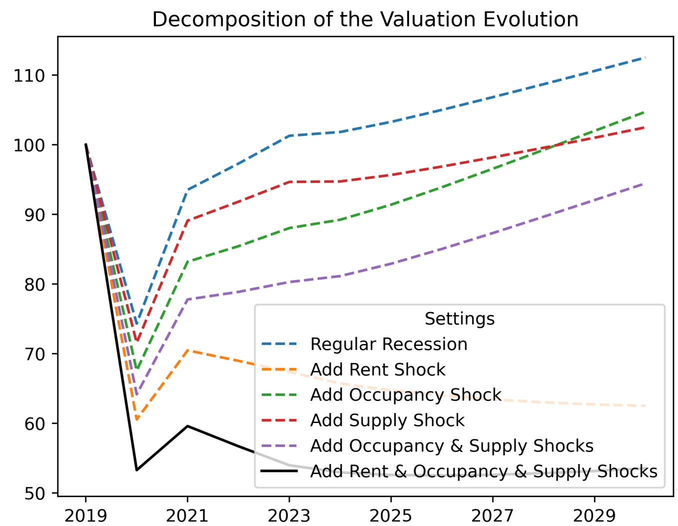
D2 Decomposition of the Effect of WFH

We now perform a decomposition of the office valuation decline in our benchmark model. WFH reduces the office valuation through three channels: (1) lower rent growth (ε), (2) lower renewal and vacancy reduction rates (s^O and s^V), and (3) lower supply growth (η). These three forces vary in quantitative significance and dynamics. Figure A13 show the valuation path for the NYC All market turning on and off various aspects of the WFH shock. The solid black line is the valuation path of our benchmark model with all aspects of the WFH shock present. The dashed blue line shows the valuation path under the business cycle realization from 2020 to 2023, but turning off all effects from WFH. It serves as the starting point for the WFH decomposition.

We first examine the role of each of the three parameter changes separately, adding one effect at a time. These results are shown as the orange line (only rent growth effect), green line 9only occupancy/vacancy effect), and red line (only supply effect). We have two main observations. First, the effects of rent growth and supply growth increase over time, while the effect of occupancy changes (slower renewal and vacancy reductions) grows at first and then reverses. The high vacancy brought by WFH is transitory. Second, the reduction in rent growth plays the largest quantitative role in reducing office values. In the short-run, rent growth, occupancy, and supply shocks account for 59.2%, 29.0%, and 11.8%, respectively, of the valuation gap between the blue and the black lines. In the long-run, rent growth, occupancy, and supply shocks account for 73.7%, 11.5%, and 14.8%, respectively, of the total impact.

We next group the occupancy and supply shocks into a single quantity shock, and then conduct a price-quantity decomposition of the WFH effect. The purple line shows the quantity impact, which is weaker than the price impact captured by the orange line: In the short-run, price and quantity shocks account for 57.5% and 42.5%, respectively, of the total impact. The difference becomes larger in the long-run (73.5% price vs. 26.5% quantity). Price declines absorb more of the negative impact of WFH as the office market slowly converges to the long-term balanced growth path.

Figure A13: Decomposing WFH Effect by Parameter Sets



Notes: This Figure illustrates how valuation estimates of all New York City offices change under different subsets of the remote work shocks. Our baseline estimate with all shocks is shown in black. Dotted lines show how valuations change when only a subset of the shocks are included.

D3 Model Results for NYC A+ Market

Table A7 shows the calibration of the cash-flow parameters for the A+ market segment, following the algorithm outlined in Appendix C2. Additionally, χ is set to be 0.12 to match the higher average lease duration of 8.28 years of A+ leases in NYC. Naturally, the state transition and SDF matrices are the same for all properties.

Table A8 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 vacancy levels than the NYC market as a whole, on average as well as in the WFH states.

Table A7: Calibration for NYC A+

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0732	-0.1328	0.0120	-0.0753
Supply growth	η	-0.0107	-0.0036	-0.0207	-0.0136
Lease renewal share	s^O	0.8884	0.6251	0.6854	0.4823
New leasing share	s^V	0.1080	0.1836	0.0833	0.1417

Table A8: Model Solution for NYC A+ Calibration

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.0534	0.0506	0.0666	0.0553	0.0646
Office $\mathbb{E}[Ret]-1$	0.0853	0.0667	0.1719	0.0416	0.1204
Office RP = $\mathbb{E}[Ret]-1-R_f$	0.0799	0.0678	0.1347	0.0428	0.0832
$\mathbb{E}[g_t]$	0.0243	0.0329	-0.0158	-0.0160	-0.0339
Vacancy rate $=1-\widehat{Q}^O$	0.0722	0.0650	0.1060	0.1366	0.1649
$\widehat{\text{Rev}}$	0.7800	0.7788	0.7857	0.7852	0.7832
$\widehat{\text{Cost}}$	0.3660	0.3650	0.3705	0.3750	0.3786
$\widehat{\text{NOI}}=\widehat{\text{Rev}}-\widehat{\text{Cost}}$	0.4141	0.4138	0.4152	0.4102	0.4046
$\widehat{V}^R$	14.7823	15.0660	13.4626	14.2113	12.8541
$\widehat{V}^C$	7.0169	7.1463	6.4146	6.8632	6.2439
$\widehat{V}=\widehat{V}^R-\widehat{V}^C$	7.7655	7.9197	7.0480	7.3481	6.6102

D4 Calibration to Other Markets

We repeat the calibration procedure discussed in the main text and in Appendix C for San Francisco and Charlotte. We use CompStak data to measure market rent growth, ε, before and during the pandemic. We also use CompStak data to measure pre-pandemic office construction rates (η is the construction minus the depreciation rate). Like in the NYC calibration, net supply growth rates during the transition (WFH-R and WFH-E) are set equal to their pre-2020 counterparts (R and E) minus an adjustment factor $\delta\eta$, set equal to the NYC one. Due to the incomplete building coverage in CompStak, estimation of η for San Francisco and Charlotte starts in 1980. We use contractual occupancy rate data from Cushman and Wakefield to calibrate s^O and s^V.[27] 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 A9 shows the calibrated parameters for San Francisco and Table A10 those for Charlotte. Tables

[27]The Cushman and Wakefield data of SF and Charlotte starts from 2008 and 2014. We impute their occupancy between 2005 and the sample start by regressing Cushman and Wakefield occupancy on log NER and city fixed effects in the top 20 city sample. We use 82% as the empirical min for SF based on the estimation from Krainer et al. (2001), and we use 80.6% for Charlotte based on https://www2.census.gov/library/publications/1997/compendia/statab/117ed/tables/construc.pdf.

A11 and A12 show the main moments for San Francisco and Charlotte, 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. Charlotte is less risky than the SF market. Figure A14 plots fan charts for occupancy rates, revenues, NOI and cap rates for San Francisco and Charlotte.

Table A9: Calibration for San Francisco

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0976	-0.1761	-0.0759	-0.2175
Supply growth	η	-0.0161	-0.0118	-0.0261	-0.0218
Lease renewal share	s^O	0.8651	0.4634	0.3896	0.2087
New leasing share	s^V	0.2338	0.4467	0.1053	0.2012

Table A10: Calibration for Charlotte

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0396	-0.2125	0.0318	-0.1673
Supply growth	η	0.0068	0.0094	-0.0032	-0.0006
Lease renewal share	s^O	0.9409	0.6784	0.6057	0.4367
New leasing share	s^V	0.2727	0.2821	0.1756	0.1816

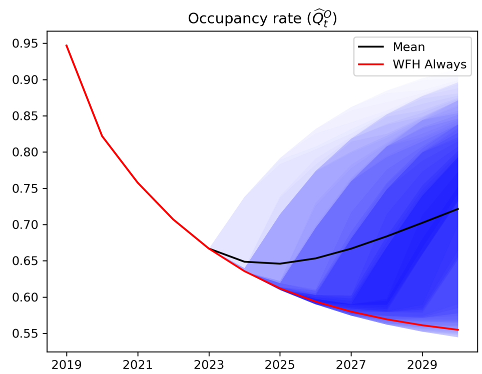
Table A11: Model Solution for San Francisco Calibration

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.0723	0.0678	0.0930	0.0861	0.1129
Office $\mathbb{E}[Ret]-1$	0.1149	0.0904	0.2290	0.0542	0.1431
Office RP = $\mathbb{E}[Ret]-1-R_f$	0.1095	0.0915	0.1919	0.0554	0.1059
$\mathbb{E}\left[g_t\right]$	0.0290	0.0431	-0.0368	-0.1085	-0.1209
Vacancy rate $= 1-\widehat{Q}^O$	0.0865	0.0736	0.1466	0.3616	0.3640
$\widehat{\text{Rev}}$	0.8236	0.8307	0.7906	0.8071	0.8452
$\widehat{\text{Cost}}$	0.4017	0.4042	0.3900	0.4624	0.4820
$\widehat{\text{NOI}}=\widehat{\text{Rev}}-\widehat{\text{Cost}}$	0.4219	0.4265	0.4006	0.3447	0.3631
$\widehat{V}^R$	11.5461	11.8869	9.9607	8.4146	7.8296
$\widehat{V}^C$	5.6735	5.8382	4.9074	4.4783	4.1688
$\widehat{V}=\widehat{V}^R-\widehat{V}^C$	5.8726	6.0487	5.0533	3.9362	3.6608

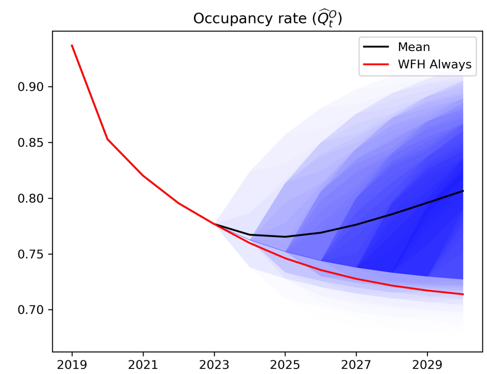
Table A12: Model Solution for Charlotte Calibration

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.0891	0.0839	0.1130	0.0741	0.0966
Office $\mathbb{E}[Ret]-1$	0.0968	0.0765	0.1912	0.0688	0.1781
Office RP = $\mathbb{E}[Ret]-1-R_f$	0.0914	0.0777	0.1541	0.0699	0.1409
$\mathbb{E}\left[g_t\right]$	-0.0020	0.0099	-0.0574	-0.0194	-0.0648
Vacancy rate $= 1-\widehat{Q}^O$	0.0874	0.0774	0.1340	0.2376	0.2732
$\widehat{\text{Rev}}$	0.9924	0.9922	0.9934	0.8162	0.8098
$\widehat{\text{Cost}}$	0.4763	0.4757	0.4792	0.4229	0.4241
$\widehat{\text{NOI}}=\widehat{\text{Rev}}-\widehat{\text{Cost}}$	0.5161	0.5165	0.5142	0.3933	0.3857
$\widehat{V}^R$	11.1867	11.3711	10.3292	10.2008	9.0674
$\widehat{V}^C$	5.3973	5.4835	4.9960	5.1931	4.6468
$\widehat{V}=\widehat{V}^R-\widehat{V}^C$	5.7894	5.8875	5.3332	5.0077	4.4206

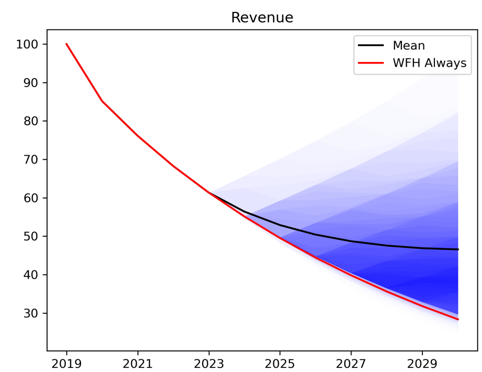
Figure A14: Fan Charts for San Francisco and Charlotte



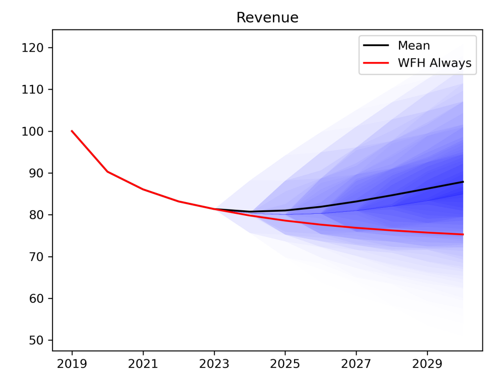
(a) San Francisco: Occupancy



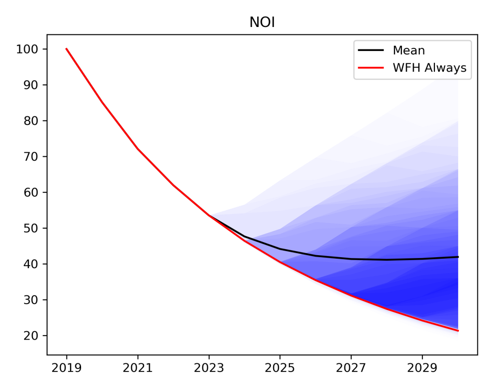
(b) Charlotte: Occupancy



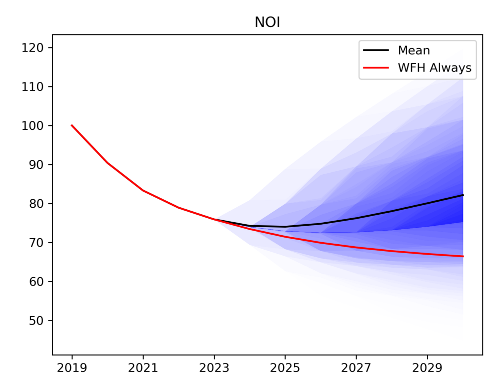
(c) San Francisco: Revenue



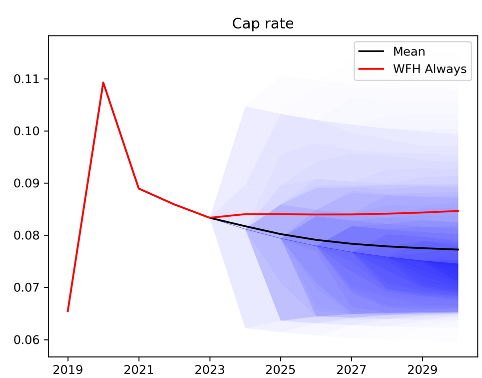
(d) Charlotte: Revenue



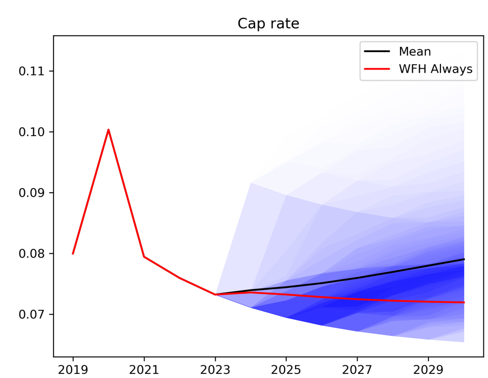
(e) San Francisco: NOI



(f) Charlotte: NOI



(g) San Francisco: Cap Rate



(h) Charlotte: Cap Rate

D5 Counterfactual Analysis of WFH Intensity in NYC

This appendix discusses the model counterfactual varying WFH at the intensive margin. We consider variations in the number of weekly WFH days (from 2.5 days more to 2.5 days fewer per week than in the benchmark model) and simulate the counterfactual office price changes.

To discipline this exercise, we utilize the reduced-form estimates of the impact of WFH on city occupancy rates and NER. We expect heterogeneity in the treatment effect of firms' WFH plans on occupancy and rents across cities. Intuitively, firms in cities with high-population density may find it more costly to not share desks among hybrid workers or to increase the amount of common spaces. Indeed, Table A13 shows stronger treatment effects of variation in the remote working index on occupancy and rent in high-density areas. Since our baseline model is calibrated to high-density New York City, we use the sum of the estimates in the first and last rows of columns (2) and (4). We get similar results if we do not consider the heterogeneity by density or if we capture the heterogeneity using MSA-level commute times instead.

Table A13: Remote Work and Office Space Demand/Rent

	Occupancy (1)	Occupancy (2)	Rent (3)	Rent (4)
Remote Work Index	-6.904	-4.896	-6.714	-2.797
	(5.278)	(5.357)	(6.070)	(6.730)
Remote Work Index $\times$ Medium Pop Density		-0.702		-2.337
		(1.505)		(3.461)
Remote Work Index $\times$ High Pop Density		-3.325*		-3.194
		(1.963)		(4.248)
N	63	60	91	80

Notes: This table shows the relationship between remote work plans and change in office space demand/office rent at the city level. In column (1) and (2), we measure change in office demand by comparing firm's total leased square footage in December 2023 against the amount leased in December 2019. In column (3) and (4), we use the city-level average rent change from 2019 to 2023 in CompStak. We remove the tenant industry, renewal, and submarket fixed effects from the deflated net effective rent, and then weight by transaction sq. ft. to calculate the average rent. Our remote work index collapses plans into three levels (4–5 days a week in person, 2–3 days a week, and 0–1 days a week). A one unit increase therefore corresponds to allowing two additional remote days a week. We define each city's population density as high (medium) if its population density is higher than the 75th percentile (between the 25th and 75th percentile). All observations are weighted based on the employment share of each city. Heteroskedasticity-robust standard errors are reported in parentheses.

We use these occupancy and rent sensitivity coefficients for high-density areas to re-calibrate the model parameters (ε, δ) under different counterfactual WFH days in NYC. For supply growth, we assume that each additional WFH day will reduce supply growth by -0.5% ($\Delta\eta$). Table A14 reports the resulting parameters for each change in WFH days relative to the benchmark. The row "0.0" is the benchmark model. All these model variants have the same parameter p. The parameter variations kick in in 2020, after the economy has entered the WFH transition.

Table A14: Counterfactual Calibration for NYC All

	ϵ		η		s^o		s^v	
ΔWFH Days	WFHE	WFHR	WFHE	WFHR	WFHE	WFHR	WFHE	WFHR
-2.5	-0.001	-0.154	-0.013	-0.012	0.765	0.337	0.161	0.275
-2.0	-0.005	-0.158	-0.015	-0.014	0.699	0.308	0.147	0.251
-1.5	-0.009	-0.162	-0.018	-0.017	0.635	0.280	0.134	0.228
-1.0	-0.013	-0.166	-0.020	-0.019	0.572	0.252	0.120	0.205
-0.5	-0.017	-0.170	-0.023	-0.022	0.510	0.225	0.107	0.183
0.0	-0.021	-0.174	-0.025	-0.024	0.450	0.198	0.095	0.162
0.5	-0.025	-0.178	-0.028	-0.027	0.391	0.172	0.082	0.140
1.0	-0.029	-0.182	-0.030	-0.029	0.333	0.147	0.070	0.119
1.5	-0.033	-0.186	-0.033	-0.032	0.276	0.122	0.058	0.099

Notes: This table presents the recalibrated model parameters for the New York City All office market under various work-from-home (WFH) scenarios. It shows how key model parameters (ε, η, s^o, s^v) change in both WFH-Expansion (WFHE) and WFH-Recession (WFHR) states as the number of WFH days is varied on the intensive margin from 2.5 days fewer to 1.5 days more than the benchmark model. The parameters reflect adjustments in demand elasticity (ε), supply growth (η), and office leasing rates (s^o, s^v) based on the counterfactual analysis of WFH intensity.

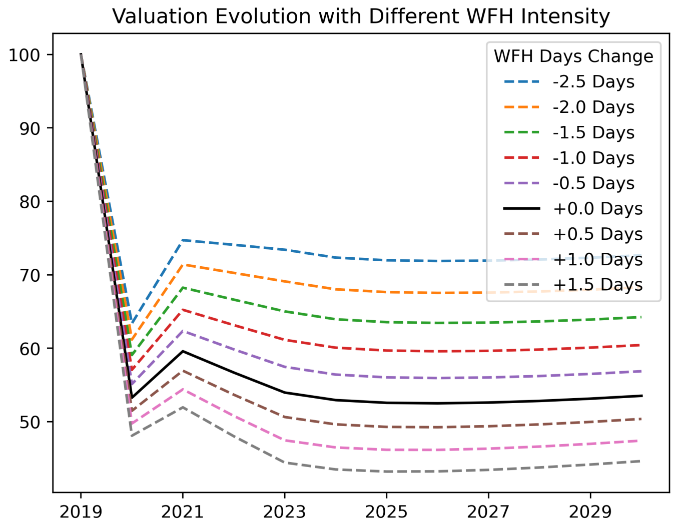
Figure A15 shows the results for the mean office valuation in the NYC All market. As always, they are conditional on the state of the economy in 2020 being WFH-R and the states in 2021–2023 being WFH-E. Recall that the Kastle data shows that the physical office occupancy in NYC is around 50% at the end of 2023, suggesting that the average office tenant in NYC may have an average of 2.5 remote working days. The valuation drop after the WFH shock shrinks significantly when the average WFH days are reduced by a day or more.[28] Conversely, each additional remote work day relative to the benchmark model further lowers office values. In conclusion, this exercise shows that intensive-margin variation in working-from-home days has large implications for office values.

D6 Sensitivity to Expected Length of Transition

Figure A16 plots the NYC office value decline in 2020 for various values of the parameter p, indicated on the top horizontal axis. The bottom horizontal axis reports the expected length of the transition, $(1-p)^{-1}$. The vertical dashed line indicates our benchmark model with $\mathbf{p} = 0.875$, which produces a 46.73% valuation decline in the transition.

[28] We still observe a moderately negative impact of WFH in the counterfactual where WFH is reduced by 2.5 days. This is not surprising given the counterfactual parameters reported in A14. The rent growth in the -2.5 days model is higher than in the baseline, but not by enough to return the model to the pre-pandemic valuation. This is probably because the regression analysis does not control for all of the relevant heterogeneity in the treatment effect.

Figure A15: WFH Intensity Counterfactual Analysis



Notes: This Figure illustrates the results of a counterfactual analysis showing how changes in the average number of work-from-home (WFH) days affect mean office valuations in the New York City All market. The analysis considers scenarios ranging from 2.5 fewer WFH days to 1.5 more WFH days compared to the benchmark model, each of which are shown in a different dotted line. The valuation paths are conditional on the economy being in a WFH-R state in 2020 and WFH-E states from 2021–2023. These results are based on the alternate calibration shown in Table A14.

D7 Sensitivity to WFH-R Rent Growth

Figure A17 shows the office valuation for NYC All for the average sample path under an alternative assumption on NER growth in the WFH-R state, namely that it equals the NER growth in a regular recession state R. The impact on the model prediction is modest.

D8 Priced Transition Risk

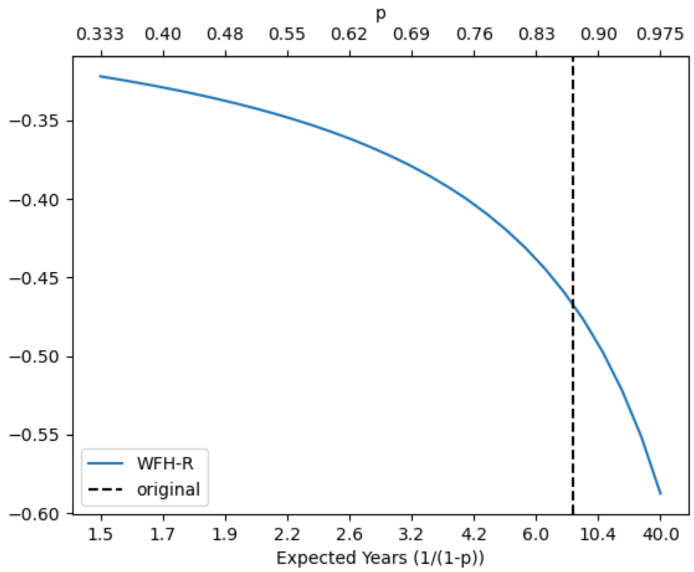
We now consider the possibility that the WFH transition period is associated with higher or lower risk premia. A positive WFH risk premium means that the WFH transition period is a bad state of the world with high marginal utility growth for the representative investor, whereas a negative risk premium means it is a good state of the world.

The one-period SDF is then determined by both the price of business cycle risk M^{BC} and the WFH risk shifter M^{WFH}:

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

To keep this calibration simple, we assume that the WFH transition risk increases the equity risk premium by a constant amount rp_{wfh}, and back out the restrictions on $M^{WFH}(z'|z)$ for each state(z, z')

Figure A16: Change in Valuation with Different p for All NYC



Notes: This Figure illustrates how the value of New York City office real estate changes in 2020 relative to 2019 for different values of the persistence parameter p. The bottom horizontal axis reports the expected length of the transition, $(1-p)^{-1}$. The vertical dashed line indicates our benchmark model with $\mathbf{p} = 0.875$.

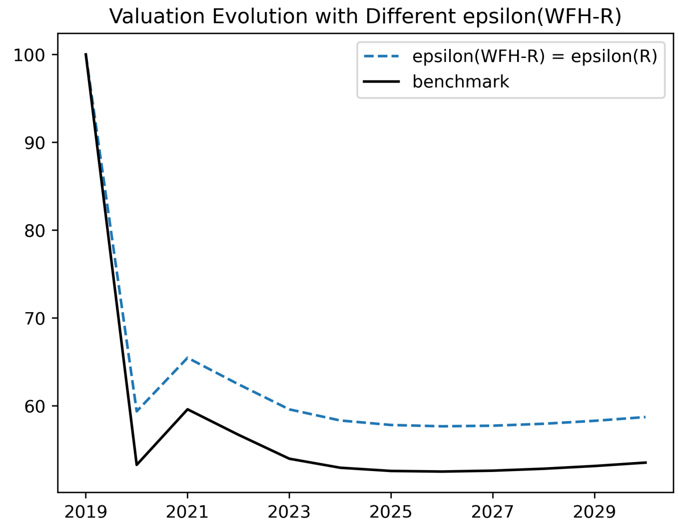
that accomplish this.[29] We consider a plausible range for rp_{wfh} ranging from -1% to 5% per year. When the rp_{wfh} is positive, WFH transition states are bad states of the world and high marginal-utility states for the representative agent. Cash flows in the WFH transition period are then more valuable: $M_{TT} > M_{TN}$. This scenario is consistent with the inference in Monte et al. (2023) based on a structural urban model, who argue that the shift to more WFH reduced aggregate welfare.

The return transition matrix is modified so that the expected return conditional on being in the transition expansion state (WFH-E) is higher than the corresponding expected return in the expansion state (E) by an amount exactly equal to rp_{wfh}, and the expected return conditional on being in the transition recession state (WFH-R) is also higher than the corresponding expected return in the recession state (R) by an amount exactly equal to rp_{wfh}. This is accomplished as follows:

$$
\begin{array}{r c}
 & \begin{array}{cccc} \text{Normal-E} & \text{Normal-R} & \text{Transition-E} & \text{Transition-R} \end{array} \\
\begin{array}{r} \text{Normal-E} \\ \text{Normal-R} \\ \text{Transition-E} \\ \text{Transition-R} \end{array} &
\begin{bmatrix}
R_{EE} & R_{ER} & \multicolumn{2}{c}{\text{Not relevant}^{30}} \\
R_{RE} & R_{RR} & & \\
R_{EE} + \frac{1+p}{1-p} rp_{wfh} & R_{ER} + \frac{1+p}{1-p} rp_{wfh} & R_{EE} - rp_{wfh} & R_{ER} - rp_{wfh} \\
R_{RE} + \frac{1+p}{1-p} rp_{wfh} & R_{RR} + \frac{1+p}{1-p} rp_{wfh} & R_{RE} - rp_{wfh} & R_{RR} - rp_{wfh}
\end{bmatrix}
\end{array}
$$

[29] Earlier versions of this paper inferred $M^{WFH}(z'|z)$ from the cross-sectional variation in the exposure of different office REIT returns to a long-short stock return factor that captured exposure to WFH shocks.

Figure A17: Setting $\epsilon(WFH - R) = \epsilon(R)$



Notes: This Figure shows how our results differ if we assume that rent growth in the WFH-Recession state ($\epsilon(WFH - R)$) does not change, but instead remains the same as rent growth in Recession states prior to remote work ($\epsilon(R)$).

Note how the realized returns conditional on remaining in the transition are lower (by rp_{wfh}) while the returns conditional on exiting the transition are higher (by $\frac{1+p}{1-p} rp_{wfh}$).

We use this return transition return matrix to pin down M^{WFH}:

$$M^{\text{WFH}} = \begin{bmatrix} M_{NN} & M_{NT} \\ M_{TN} & M_{TT} \end{bmatrix}$$

Since the probability of transitioning from the E or R states to the WFH-E and WFH-R is zero, the Euler equations for the stock return in the E and R states are uninformative for M^{WFH}. Hence, we normalize $M_{NN} = M_{NT} = 1$. The remaining two parameters M_{TN} and M_{TT} enter in four Euler equations: the Euler equation for the equity return in the WFH-E state, the Euler equation for the equity return in the WFH-R state, the Euler equation for the risk-free rate in the WFH-E state, and the Euler equation for the risk-free rate in the WFH-E state. We choose the values for M_{TN} and M_{TT} that minimize the root mean squared stock Euler equation errors and the risk-free rate errors, weighting the WFH-E moments by 0.823 and the WFH-R moments by 0.177, which are the relative likelihoods of expansions and recessions. It turns out that we can set $M_{TT} = 1$ without increasing these four Euler Equation errors. The first column in Table A15 reports the best-fitting remaining parameter M_{TN}, while the second column reports the weighted

[30] This part of the return transition matrix is irrelevant for the calibration of M^{WFH} since the probability of entering the WFH transition period is zero from the E and R states.

Table A15: Calibration Result of WFH Transition Risk

rp_{wfh}	M_{NT}	RMSE (%)	ΔV_{2020} (%)	ΔV_{2030}(%)
-1%	1.0388	0.5280	-45.30	-46.11
0%	1	0	-46.73	-46.47
1%	0.9605	0.4714	-48.18	-46.84
2%	0.9236	0.8730	-49.54	-47.19
3%	0.8897	1.2212	-50.79	-47.51
4%	0.8589	1.5241	-51.92	-47.79
5%	0.8311	1.7888	-52.95	-48.05

root mean squared error in percent per year.

Generally, the fit for the two Euler equations for the equity market in the WFH-E and WFH-R state is excellent. Most of the RMSE budget is spent on the interest rate, which tends to be a bit higher in the WFH-E and WFH-R states than in the baseline model. This may not be undesirable, given that interest rates in the U.S. economy were high in 2022 and 2023.

The last two columns of the table show what the model with priced transition risk implies for the immediate value drop (2020 versus 2019) and for the long-run value drop (2030 versus 2019) of the NYC All office stock. The first row with $rp_{wfh} = 0$ is the benchmark model.

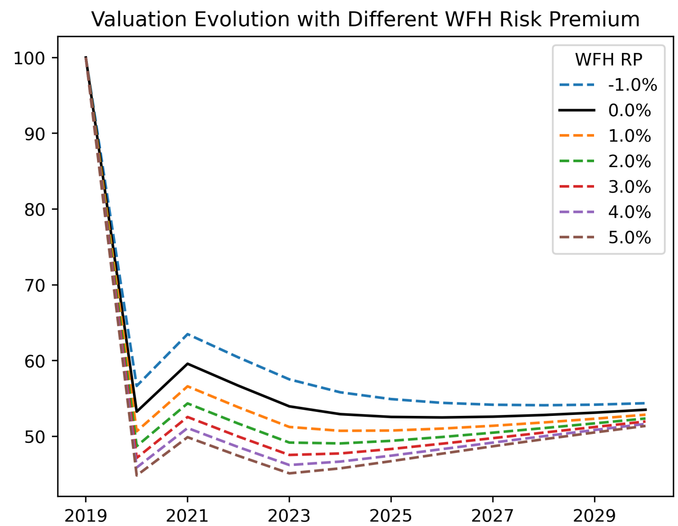
Figure A18 shows the office valuation of NYC for WFH risk premium values from -1% to 5% per year. Intuitively, higher WFH risk premium represents that WFH is a worse state, and thus the office market has a lower valuation. The office market provides higher total return (NOI + capital gain) required by the market through adjusting to a lower value at first. We can also observe that priced WFH risk has low quantitative importance for our result: The average valuation paths of different WFH risk premia stay close to the benchmark case (0% risk premium), and eventually converge to the benchmark in the long-run. The evolution of the cash flow dominates the valuation of the office market during and after the WFH transition period.

D9 Shutting Down Business Cycle Risk

Figure A19 shows the valuation impact in a model where the pricing of cash flow is independent from the business cycle. We compute this model by setting M^{BC} such that we match the same unconditional equity return of 11.08% in both expansions and recessions, and that the state prices in all four transition states are the same.[31] The impact on the value decline of NYC office is -41.90% in 2020 and -46.65% in

[31] We choose to apply a fixed risk premium to the cash flow instead of directly using the risk free rate as the discount rate because the cash flow growth in our model is higher than the risk free rate (see Table A6 for details), and thus we need to add

Figure A18: NYC All Valuation with Priced WFH Risk



Notes: This Figure illustrates how valuation estimates of all New York City offices change under different assumptions of risk premium associated with remote work. Our baseline estimate, shown in black, assumes no change in risk premia. Dotted lines show how valuations change in percent point increments of different risk premia.

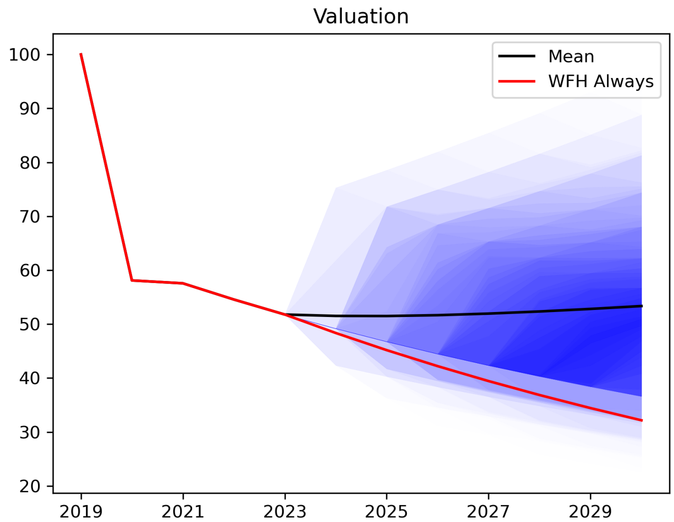
2030, relative to pre-pandemic levels. The corresponding numbers in the benchmark model are -46.73% and -46.47%. The slightly smaller short-term valuation effect arises because the state-invariant business cycle (equity) risk premia raise the discount rate in expansion, and thus leads to shorter effective duration of the stream of office cash flows in 2019, which weakens the valuation impact of a given decline in cash flows. Indeed, the cap rate in 2019 is 9.14% in this model compared with 5.78% in the benchmark model. This difference in the valuation impact narrows in the long-term, because the unconditional discount rate is the same as the one in the benchmark model.

D10 Fixed WFH Transition Length

The office market exits the WFH transition period with probability $1 - p = 12.5\%$ each period in our benchmark model. We now disentangle the impact of the transition from the uncertainty about the length of the transition period. We calibrate an alternative model for the NYC All office market with an ex-ante deterministic length of the WFH transition period. Starting from the value function of 0 remaining years (ry) in the WFH transition period, we iteratively solve for the value function with

a risk premium to prevent the valuation functions from having infinite values.

Figure A19: Shutting Down the Business Cycle Risk



Notes: This Figure shows how our results change under a model in which business cycle risk is shut down. We compute this model by setting M^{BC} such that we match the same unconditional equity return of 11.08% in both expansions and recessions, and that the state prices in all four transition states are the same.

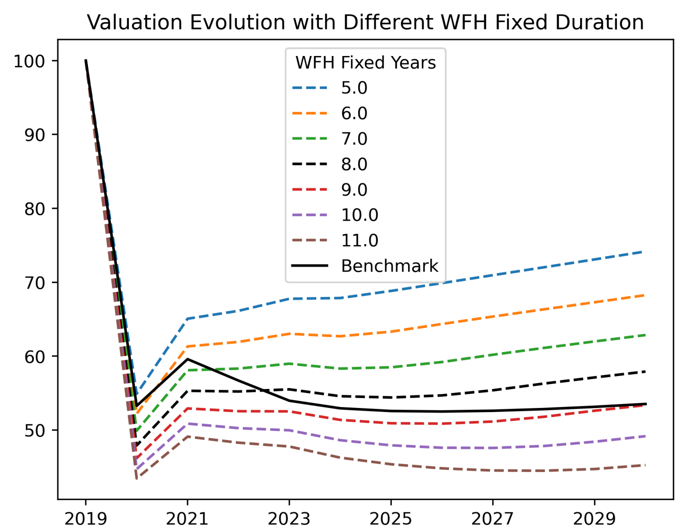
$ry = 1, 2, 3, ...$ remaining years in the WFH transition period using backward induction:

$$\hat{V}\left(ry, z, \hat{Q}, \hat{R}\right) = \mathbb{E}\left[M(z')\left[\widehat{NOI}\left(z', \hat{Q}', \hat{R}'\right) + \hat{V}\left(ry - 1, z', \hat{Q}', \hat{R}'\right)\right]\right].$$

Figure A20 shows the mean office valuation in the NYC All market, conditional on the state of the economy in 2020 being WFH-R and the states in 2021–2023 being WFH-E. The average office value decline is modestly higher when the transition ends in $1/(1-p) = 8$ years for certain (-52.09% in 2020 vs. -46.47% in the benchmark model). The opportunity of early exit is more valuable than the protection from late exit, so that the uncertainty about the length of the transition period ends up benefiting the valuation. This is because vacancy growth decelerates while the strength of reversal accumulates with more time in the WFH transition period.

In 2020, the certainty equivalent of the uncertain transition length is around 5 years.The mean valuation path of the benchmark model (solid black line) overlaps with the mean valuation path under fixed transition length of 6 years (dashed orange line), which has 5 years remaining in transition at the end of 2020. The certainty equivalent changes over time. It drops to around 4.5 years at the end of 2023, with the benchmark's solid black line halfway in between the dashed black line (8 years of transition, 4 years of transition remaining at the end of in 2023) and dashed red line (9 years of transition, 5 years of transition remaining at the end of in 2023).[32] The upside of uncertainty (exit out of the transition) becomes more valuable than the downside (staying in transition) over time. However, note that we are only examining the cash flow risk of WFH transition here. If the discount rate (WFH risk premium) drops when the uncertainty about the length of the transition period is removed, the certainty equivalent of the uncertain WFH transition period will become higher. See Appendix D8 for details.

Figure A20: Fixed Length of WFH Transition Period



Notes: This Figure compares office valuation paths for New York City under different assumptions about the length of the work-from-home (WFH) transition period. In our benchmark model, office markets exit the WFH transition each period with $1 - p = 12.5\%$ probability each period. We contrast the valuation impact with a model in which the transition is ex-ante deterministic in length, and show the valuation impacts of different deterministic lengths plotted as dotted lines.

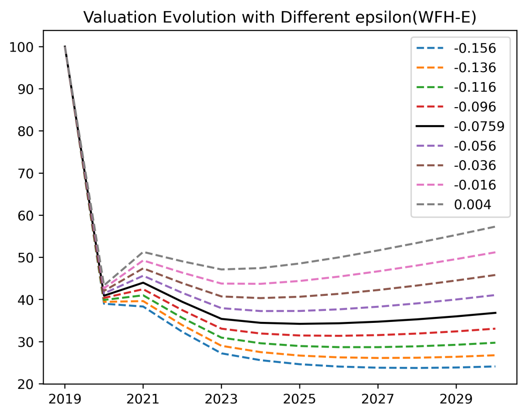
D11 Robustness Tests for San Francisco

Figure A21 performs four sensitivity analyses for San Francisco. Panel (a) varies $\varepsilon(WFH - E)$, the rent growth rate in the WFH-E state. Panel (b) varies $\Delta\eta$, the gap between net supply growth in the transition regime relative to the pre-2020 regime. Panel (c) varies the expected length of the transition period governed by the parameter p. Panel (d) introduces a floor for office values set at 30% of 2019 valuations. The latter exercise is a simple way to model additional optionality from adaptive reuse not already captured by the net supply parameter η. This specification is intended to capture the redeployability

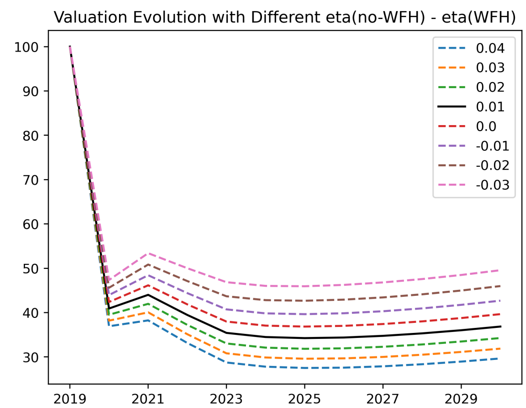
[32] Note that 2023 is the last year we can infer the certainty equivalent transition length because only years up until 2023 are in WFH transition for certain in the benchmark model. The evolution to the right of 2023 is not informative about the effect of the uncertainty about the transition period. First, the valuation path of the benchmark model (solid black line) becomes an average of both the paths that have exited WFH transition and the paths that are still in WFH transition, and thus provides noisy information regarding risk in WFH transition. Second, these points only represent the expected price of the NYC office market, and ignores the value of the cash flow paid out before.

option, as in Kim and Kung (2017) and Benmelech, Garmaise and Moskowitz (2005), as office buildings may ultimately be converted to other uses. We use 30% as a rough benchmark for the option value to covert to other uses. A fuller consideration of this option—which will be affected by interest rates, costs of conversion, and demand for other uses among other factors—is outside of the scope of our analysis, which is focused on valuing cash flows resulting from buildings operated as commercial office buildings. Gupta et al. (2023) studies conversions from office to residential in detail.

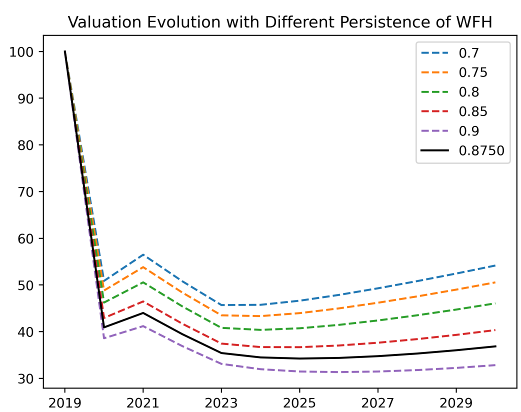
Figure A21: Robustness Tests for San Francisco



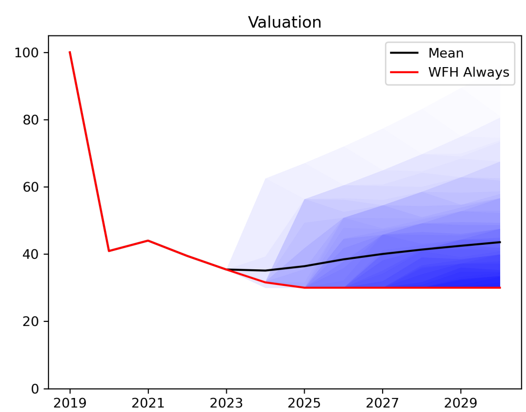
(a) Different $\epsilon(WFH - E)$



(b) Different $\eta(no - WFH) - \eta(WFH)$



(c) Different Persistence of WFH



(d) Valuation $\geq$ 30% of Pre-pandemic Valuation

Notes: This Figure presents four panels (a)–(d) showing sensitivity analyses for office valuations in San Francisco under different model assumptions. Panel (a) shows robustness under different assumptions of rent growth in the expansion state ($\epsilon(WFH - E)$). Panel (b) varies $\Delta\eta$, the gap between net supply growth in the transition regime relative to the pre-2020 regime. Panel (c) varies the expected length of the transition period governed by the parameter p. Panel (d) introduces a floor for office values set at 30% of 2019 valuations.