

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

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1 Introduction

“Commuting to office work is obsolete.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

Peter F. Drucker, 1989

The Covid-19 pandemic led to drastic changes in where people work. Physical office occupancy in the major office markets of the U.S. fell from 95% at the end of February 2020 to 10% at the end of March 2020, and has remained depressed ever since, only gradually creeping back to 47% by November 2022. In the intervening period, work-from-home (WFH) practices have become more established, with many firms announcing permanent remote or hybrid work arrangements associated with shrinking physical footprints. These shifts in current and projected future office demand have led to concerns that commercial office buildings may become a stranded asset in the wake of disruptions resulting from remote work. Because office assets are often financed with debt which resides on banks' balance sheets and in Commercial Mortgage-Backed Security (CMBS) portfolios, large declines in value would have consequences for institutional investors and for financial stability.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 doom loop that lowers the quality of life for urban residents and worsens the business environment.

In this paper, we ask what these changes in remote work arrangements imply for the value of office buildings. To answer this challenging question, we combine new data with

¹Investable commercial real estate assets were worth about \$4.7 trillion at the end of 2019, of which office represents the largest component. They make up an important part of the portfolio allocation to “real assets” of a growing number of institutional investors (Goetzmann, Spaenjers and Van Nieuwerburgh, 2021). Banks have about \$2.4 trillion in commercial real estate loans on their balance sheets as of June 2022 according to Call Report data.

a new asset pricing model. A central model ingredient is uncertainty about future WFH arrangements.

The value of office reflects the expected present discounted value of its cash flows. We begin by analyzing the shock to current cash flows. Using a unique data set from CompStak, we study lease-level data for 105 office markets throughout the United States over the period from January 2000 until May 2022. We document a 16.89 percentage point decrease in lease revenue in real terms between December 2019 and May 2022. Two-thirds of this decline reflects decreases in the quantity of in-force leases. The remainder is accounted for by declines in real rents on in-force leases. The quantity of newly-signed leases in our data set falls from 253.43 million square feet per year just before the pandemic to 59.32 million square feet in May 2022. Rents on newly-signed leases fell by 13.16% in real terms between December 2019 and December 2021 before reversing to pre-pandemic levels by the end of 2021, with meaningful heterogeneity across cities. Because a large fraction of leases in-force in early 2020 did not come up for renewal in 2020 and 2021 (61.77% in the U.S., 71.59% in New York), and vacancy rates are already at 30-year highs in several major markets (21.5% in New York in 2022.Q2), rents may not have bottomed out.

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

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

repurposed towards other uses.

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

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

A key parameter that affects the change in office valuations due to remote work is the persistence of WFH practices. We back out this parameter from the (unlevered) stock return on NYC-centric office REITs observed between December 2019 and December 2020. Since REITs predominantly invest in A+ office product, we do so for a separate calibration to the

A+ segment of the NYC office market. The model matches the 2020 (unlevered) office return for an annual persistence parameter of 0.82, indicating that office investors believe remote-work practices to be long-lasting. We show that our conclusions are robust to the specific choice of our persistence parameter.

With this parameter in hand, we return to the full NYC office market calibration. We obtain a 44.80% reduction in the value of the entire NYC office stock between December 2019 and December 2020. Simulating the model forward for ten years, we characterize the mean value of the office stock and—just as importantly—the uncertainty around this valuation, which depends on the sequence of shocks that hits the economy. Along the average path, office occupancy stabilizes and the economy returns to the no-WFH state with some probability. These mean-reversion forces push office valuations towards an average office value in 2029 that is about 39.18% below 2019 values. Along paths where the economy remains in the WFH state, office values in 2029 are 59.86% below their 2019 values. Hence, there is substantial uncertainty about future office values, *WFH risk*, that our approach quantifies.

We repeat the calibration exercise for San Francisco and Austin, the former an example of an office markets that is hit even more by remote work and the latter an example of a market that has been more resilient. Naturally we find larger valuation reductions in the former, compared to NYC, and smaller reductions in the latter. However, both markets see declines, suggesting that spatial reallocation of activity (for example, from New York City to the Sunbelt) is not entirely driving our results.

What do these numbers imply for the aggregate value of the office stock? For NYC, we observe \$17.76 billion in annual lease revenue in the CompStak data pre-pandemic and the ratio of office value to lease revenue is 6.02 based on our model. Hence, the value of the NYC office properties in our dataset is \$124.43 billion. The short-term value reduction of 44.80% amounts to \$55.75 billion, while the longer-term reduction of 39.18% amounts to \$48.75 billion. Extrapolating to all properties in the U.S. in our dataset, the \$64.86 billion annual leasing revenue results in a \$454.34 billion office value before the pandemic using the same 6.02 value-to-lease revenue ratio. We estimate that pandemic-related disruptions

around remote work have lowered the value of office buildings observed in our dataset by \$203.54 billion in the short run (44.80%) and by \$178.01 billion in the long-run (39.18%). Adjusting for incomplete data coverage, the total decline in commercial office valuation in the U.S. is estimated at \$484.00 billion in the short-run and \$413.44 billion in the long-run.²

The key takeaway from our analysis is that remote work is shaping up to massively disrupt the value of commercial office real estate in the short and medium term. These findings are informed by our results that firms appear to demand substantially less office space when they adopt remote working practices, and that such practices appear to be persistent. In the long run, firms may discover that the productivity or innovation impact from remote work is worse or better than expected, remote-work technologies may improve further, and cities may repurpose existing office assets to alternative use. These changes are likely to play out over decades and are beyond the horizon of our analysis.³

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

We also relate closely to the rapidly growing literature on the impact of remote work on real estate, surveyed in [Van Nieuwerburgh \(2022\)](#). [Rosenthal, Strange and Urrego \(2021\)](#)

²Table 6 details the coverage of CompStak data for the largest 20 markets, using the inventory data from Cushman & Wakefield as the universe. For these markets, we scale up our value change by the inverse of the market-specific coverage ratio. For the remaining 85 office markets, we divide by a common coverage ratio, chosen to reconcile the aggregate office stock in CompStak (1832.14 million square feet of active leases in our dataset in February 2020) with Cushman & Wakefield's office stock (5,375 million square feet at the end of 2019).

³That 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.

documents a decline in the commercial rent gradient in the city center and transit cities as compared to car-oriented cities with COVID-19. [Bartik, Cullen, Glaeser, Luca and Stanton \(2020\)](#); [Barrero, Bloom and Davis \(2021\)](#); [Aksoy, Barrero, Bloom, Davis, Dolls and Zárate \(2022\)](#) present survey data to assess the prevalence of remote work and investigate reasons why working from home is expected to last. [Hoesli and Malle \(2021\)](#) analyze the effect of COVID-19 on commercial real estate in the European markets. [Gupta, Mittal, Peeters and Nieuwerburgh \(2021\)](#); [Brueckner, Kahn and Lin \(2021\)](#); [Ramani and Bloom \(2021\)](#); [Mondragon and Wieland \(2022\)](#) study the impact of work from home on residential real estate prices in urban and suburban areas. [Cohen, Friedt and Lautier \(2020\)](#) shows changes in real estate prices in New York City due to COVID-19.

An important urban economics branch of this literature explores the effects of remote work in quantitative general equilibrium models of labor and real estate markets ([Delventhal, Kwon and Parkhomenko, 2021](#); [Davis, Ghent and Gregory, 2021](#); [Li and Su, 2021](#); [Gokan, Kichko, Matheson and Thisse, 2022](#)). These models are well-suited for thinking about long-run implications of remote work on city structure, including how office space could be used for alternative purposes. This paper uses micro data on office leases to document changes in commercial real estate markets with a rise in remote work, and uses these data as inputs in a new asset pricing model. The finance perspective, which places WFH risk at the core, is a useful complement to the urban economics perspective. An important challenge for future work is to integrate these two approaches.

Finally, our work relates to literature examining commercial real estate as an asset class. [Cvijanović, Milcheva and 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 in different contexts.

The rest of the paper is organized as follows. Section 2 overviews changes in the of-

fice leasing market during the pandemic, highlighting the contemporaneous losses to lease revenue. Section 3 estimates the valuation of office buildings in the context of a structural model, and 4 highlights the implications for office valuation. Section 5 concludes. Appendix A estimates changes to future expected returns in the context of an asset pricing model incorporating work-from-home risk. Appendix B provides model derivations. Appendix C details the calibration algorithm. Appendix D reports additional results from the model. Appendix E contains the calibration details for San Francisco and Austin.

2 The Office Market During the Pandemic

2.1 Data

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

Our main data set is CompStak, a data platform where commercial real estate brokers exchange leasing information. The data set contains lease-level transaction data for a large sample of offices leases in the U.S. for the period January 2000–June 2022. Data coverage improves in the first part of the sample and stabilizes around 2015.

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

terms of quantities, prices, and contract features.

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

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

We also measure hybrid work conditions for a sample of 200 firms, chosen from among the firms with the largest presence in our leasing data. We hand-classify working plans (in-person, hybrid, and fully-remote) as well as the number of anticipated days back in the office for these firms.⁴

2.2 Shock to Leasing Revenue

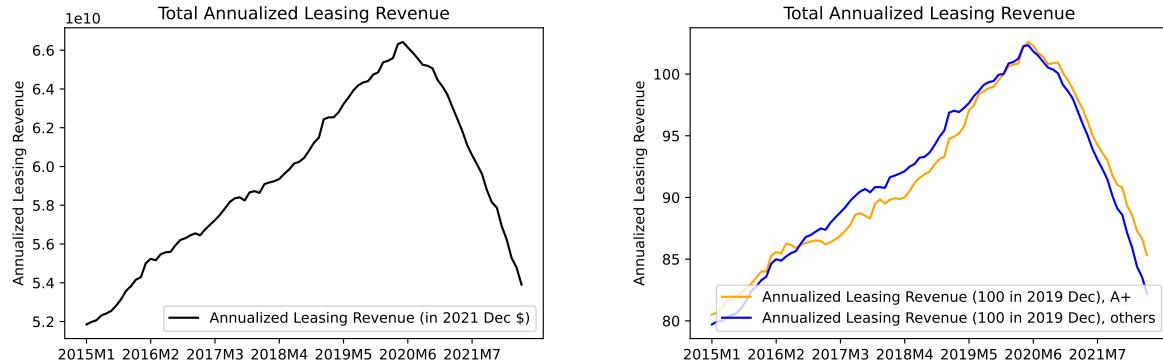
Figure 1 highlights the first component of the valuation shock: the reduction in current leasing revenue. We compute the total annual leasing revenue on all in-force leases each month, excluding subleases to avoid double-counting of revenue. The total value of annualized leasing revenue was \$64.86 billion prior to the pandemic in December 2019 (all numbers expressed in December 2021 dollars). Total leasing revenue then experienced a 16.89% decline, falling to \$53.90 billion in May 2022 (Panel A). This decline is substantial taking into account the long-term nature of commercial leases. It indicates substantial shifts in leasing activity among those tenants in a position to make a choice about their office space needs.

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

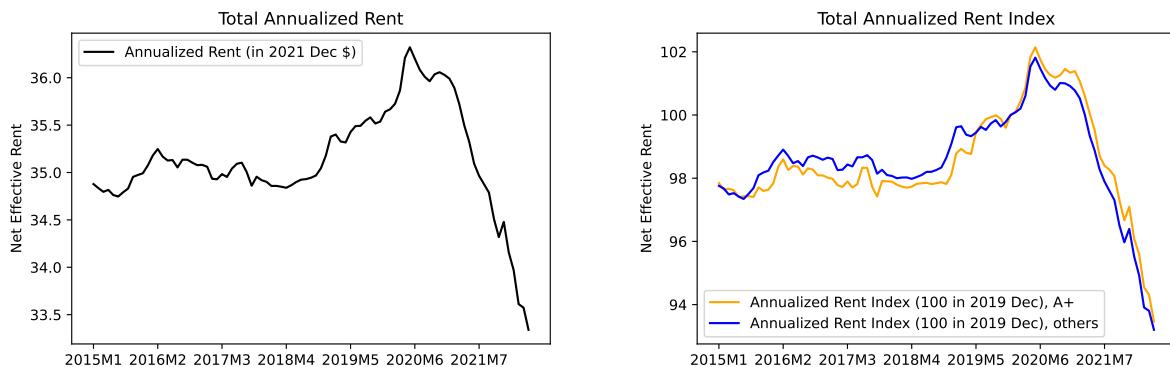
⁴We used two separate research assistants to hand-classify remote working plans, before having a third assistant reconcile the two classifications into one uniform data set.

Figure 1: Current Office Lease Revenues

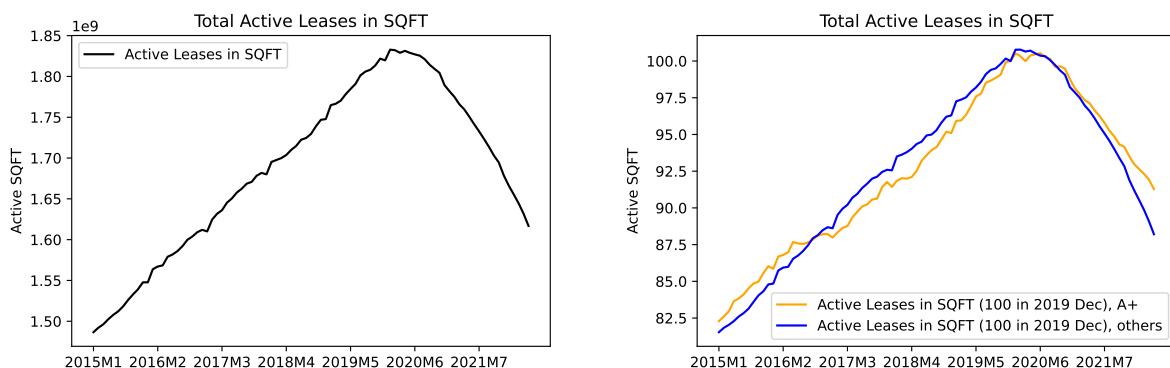
Panel A: Total Lease Revenue on In-force Contracts



Panel B: Average Rent on In-force Contracts



Panel C: Quantity of In-force Contracts



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

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

Flight To Quality in Lease Revenue

The decrease in current lease revenue is felt most strongly for lower- than for higher-quality office space. To measure high-quality buildings, we define “A+” properties by isolating leases that are in the top ten percent of NER in each quarter and submarket among all properties that are ranked as Class A by CompStak. We categorize a building that has such a lease as A+ and assume that the A+ status remains for ten years, unless another top-10% lease is signed in that building at which point the ten-year clock resets. The remaining buildings (“Other”) are classes “A-” (A without A+), B, and C. The right panels of Figure 1 separate out the two groups, normalizing the statistics for each group at 100 in December of 2019.

We see that rent increases are stronger for Class A+ buildings during the pandemic (Panel B), and the decline in active leases is smaller (Panel C). The combination of both of those forces means that total annualized leasing revenues fall by 14.69% for A+ properties versus by 17.79% for the rest of the office universe.

We observe even stronger evidence for differing trends across office space by quality in Figure 2, which focuses on New York City (NYC) and Texas, as representative examples of both major and non-major commercial real estate markets. Panels A and B display changes in NER per square foot (sf) on newly-signed leases. The left panels define A+ properties as before. The right panels use an alternative definition of high-quality buildings based on building age: younger buildings are those constructed in or after 2010. Properties defined as A+ sustain rent levels much better in both New York and Texas compared to other properties. Younger buildings even experience sizable rent increases, compared to substantial rent decreases for other properties. This divergence suggests a “flight to quality” in office demand in these markets.

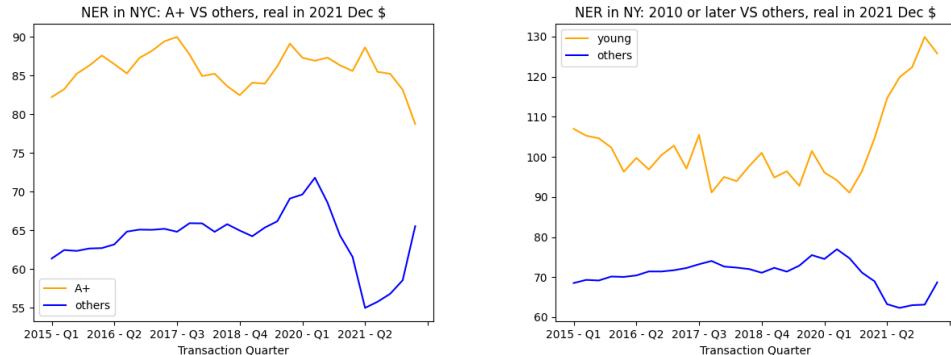
2.3 Physical Occupancy, Contractual Occupancy, and Lease Expiration

In Figure 3 (Panel A) we highlight the key shift which is the focus of our paper: the sudden drop in physical office presence for white-collar workers. Physical office occupancy is measured from turnstile data provided by Kastle.⁵ Over the course of the pandemic, 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%) by the end of 2020. It saw several more dips as the pandemic intensified in early 2021. The recovery continued in the second half of 2021 to about 40% (35%), before falling sharply due to the rise of the Omicron variant at the end of 2021. The latest data as of early November 2022 show a 47.3% occupancy rate among the largest 10 office markets (46.7% in NYC). With two and a half years of remote work experience, many employers and employees have formed

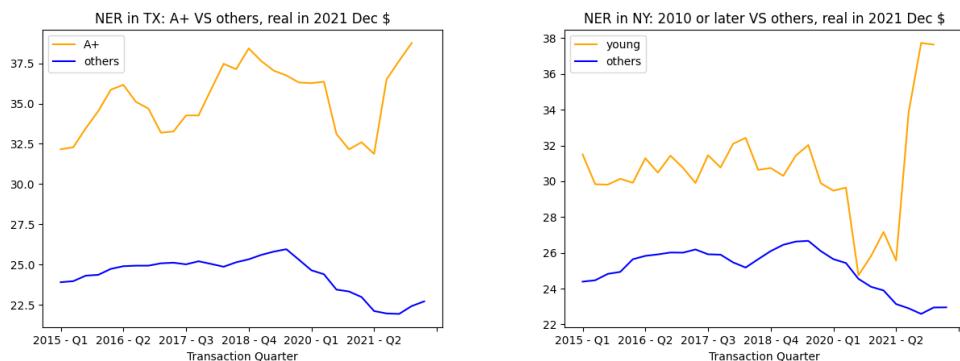
⁵The Kastle data cover more than 2,600 buildings in 138 cities.

Figure 2: Changes in Office Rents and Occupancy

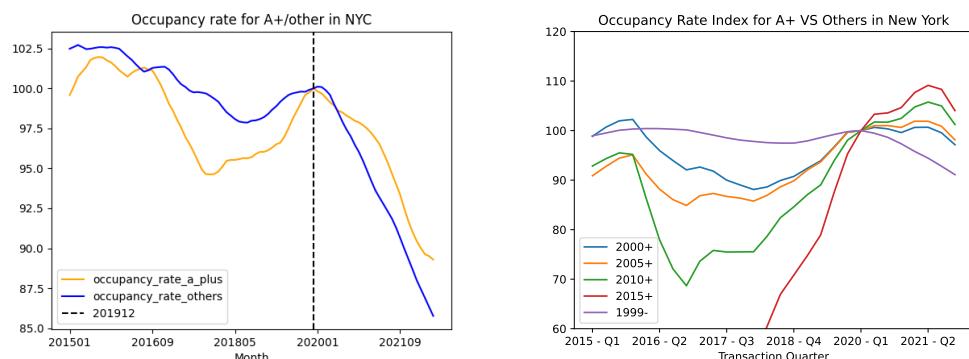
Panel A: Net Effective Rent by Quality Segment in NYC



Panel B: Net Effective Rent by Quality Segment in Texas



Panel C: Occupancy Rates by Quality Segment in New York City



Panel D: Occupancy Rates by Quality Segment in Texas

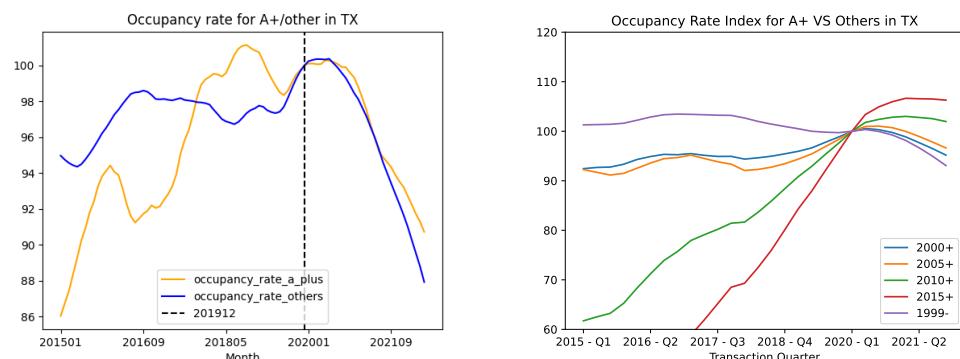
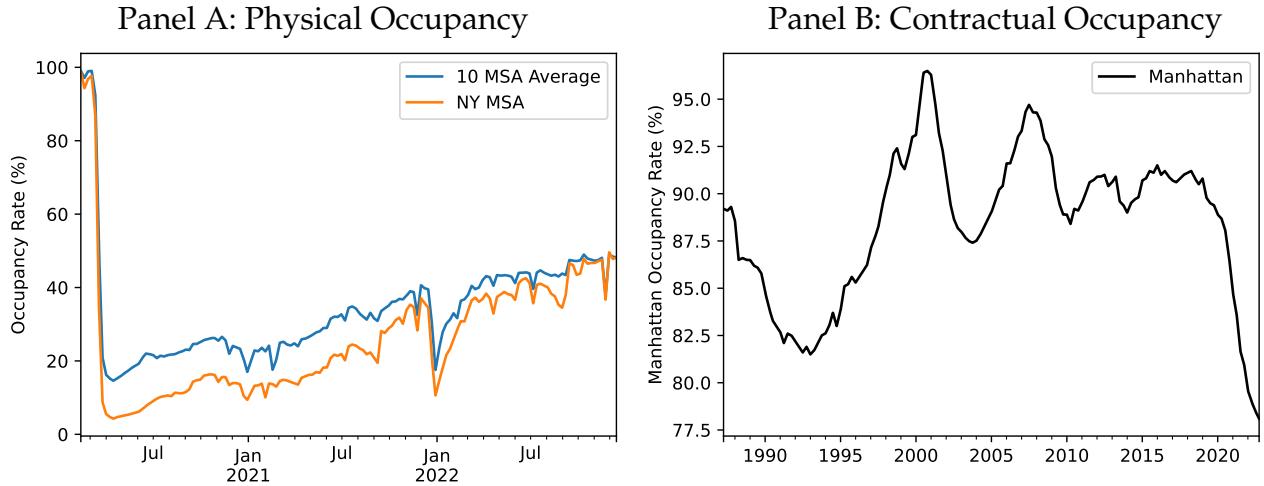


Figure 3: Office Occupancy

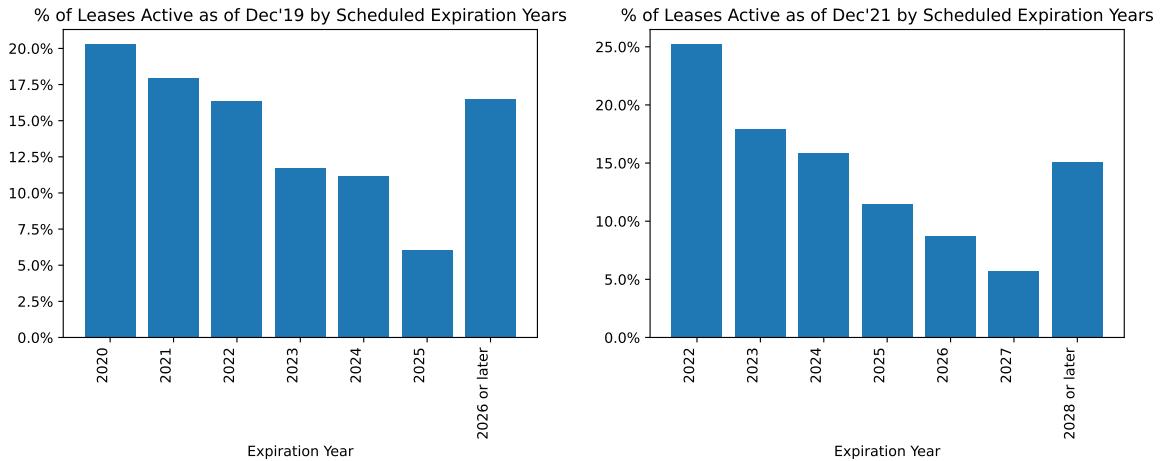


new habits and expectations. Employees have come to like remote work and report being more productive. Employers have revised upward their own longer-run expectations on average employee days in the office (Barrero et al., 2021; Aksoy et al., 2022), and have begun to adjust their demand for office space as shown in more detail below.

These large drops in physical occupancy did not translate into large immediate drops in commercial office cash flows, as shown above. The reason for the delayed and gradual reaction is the staggered nature of commercial leases, highlighted in Figure 4. Because most commercial leases are long-term, and not up for immediate renewal, only a fraction of office tenants have had to make active choices about their future office demand so far. Among all in-force leases as of the end of December 2019, only 38.23% came up for renewal in 2020 and 2021 combined. Nearly all of the tenants not up for renewal have continued to make rent payments, despite their lack of physical occupancy. When more leases come up for renewal in the future, the office demand of tenants who have made limited use of office space during the pandemic remains highly uncertain and is a crucial determinant of office valuation.

Despite the modest share of tenants that have seen lease expirations so far, we already observe drastically higher vacancy rates reflecting lease exits among that sample. The contractual occupancy rate in Manhattan, the country's largest office market, was at a 30-year low of 78.5% in the second quarter of 2022 (Cushman & Wakefield), as shown in Figure 3

Figure 4: Lease Expiration Schedule



(Panel B). Panels C and D of Figure 2 plot occupancy rates for NYC and Texas using our CompStak data, scaled to 100 in December 2019. The left panels show that occupancy rates fell for both A+ and lower-quality buildings. The right panels shows that younger buildings, those built after 2010 or after 2015, saw substantially stronger occupancy during the pandemic than older buildings.

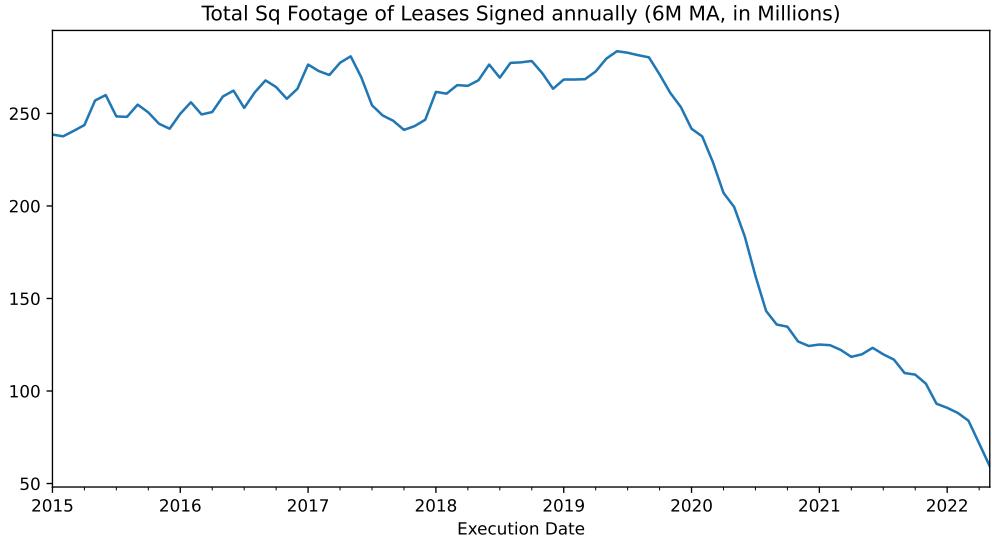
2.4 Impact on Quantities and Prices of New Leases

Pandemic Impact on New Lease Quantities

We next turn to examine the consequences of pandemic-associated shifts in office demand on the number of new leases signed. To do so, we aggregate the total number of new commercial office leases signed in the CompStak data.⁶ We observe a dramatic decrease in the quantity of new leases signed, sometimes called absorption in the industry, across both sets of markets in Figure 5. The volume of newly signed leases fell from 253.43 million sf per year in the six months before the pandemic to 59.32 million sf per year over the most recent six months. This indicates a substantial drop in office demand from tenants who are actively making space decisions.

⁶In unreported analysis, we find that the changes are similar in major and non-major office markets. The major office markets are: New York City, Philadelphia, Boston, Houston, Dallas, Austin, Nashville, Chicago, Atlanta, Miami, Washington D.C., Denver, Los Angeles, Bay Area, and San Francisco.

Figure 5: New Leases Signed



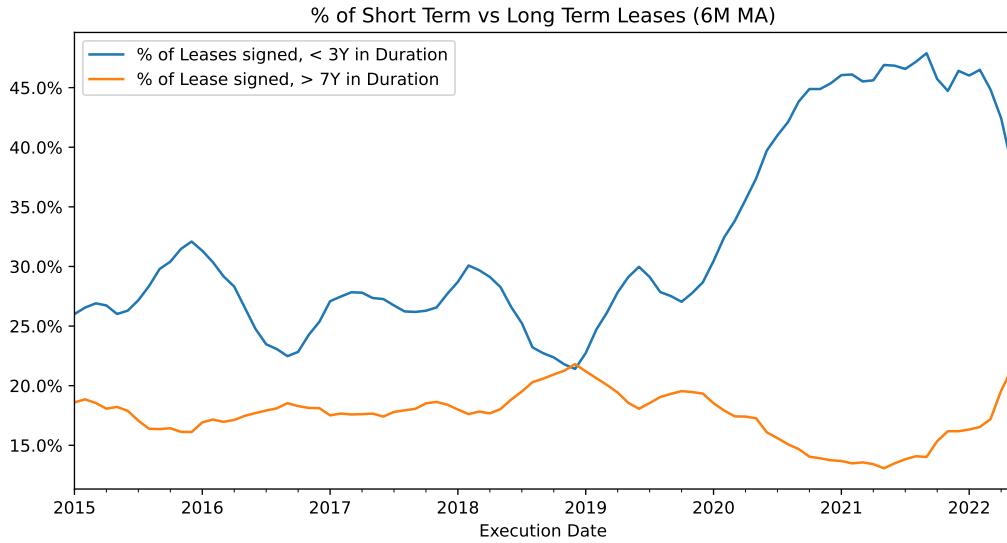
Pandemic Impact on New Lease Duration

Even when tenants do renew leases, they may not do so under the same set of terms. Figure 6 shows that the share of new leases signed that are less than three years in duration increased substantially during the pandemic, to account for almost half of our sample, while the share of leases with a duration more than seven years decreased meaningfully. The shortening of lease duration suggests important shifts in the commercial office market, even conditional on lease renewal. As a result, the coming years 2023–2025 will feature even larger than expected lease expiration from two channels: the pre-scheduled expiration of long-term leases signed before the pandemic, as well as the expiration of short-term leases signed during the pandemic. This is shown in Panel B of Figure 4.

Pandemic Impact on New Lease Rents

We next explore the dynamics of net effective rents on new leases. We compute the square-foot weighted average NER (in 2021 dollars). Figure 7 shows large changes in real NERs on new leases signed over the course of the pandemic. Panel A is for all markets and Panel B is for New York City. We provide both a longer-term perspective in the top row and zoom in on

Figure 6: Lease Duration Changes



the post-2018 period in the bottom row of each panel. Nationally, the NER fell by 13.16% in 2020. Starting in January 2021, the NER on newly-signed leases experienced a sharp reversal with the NER ending up back at its pre-pandemic level at the end of our sample.

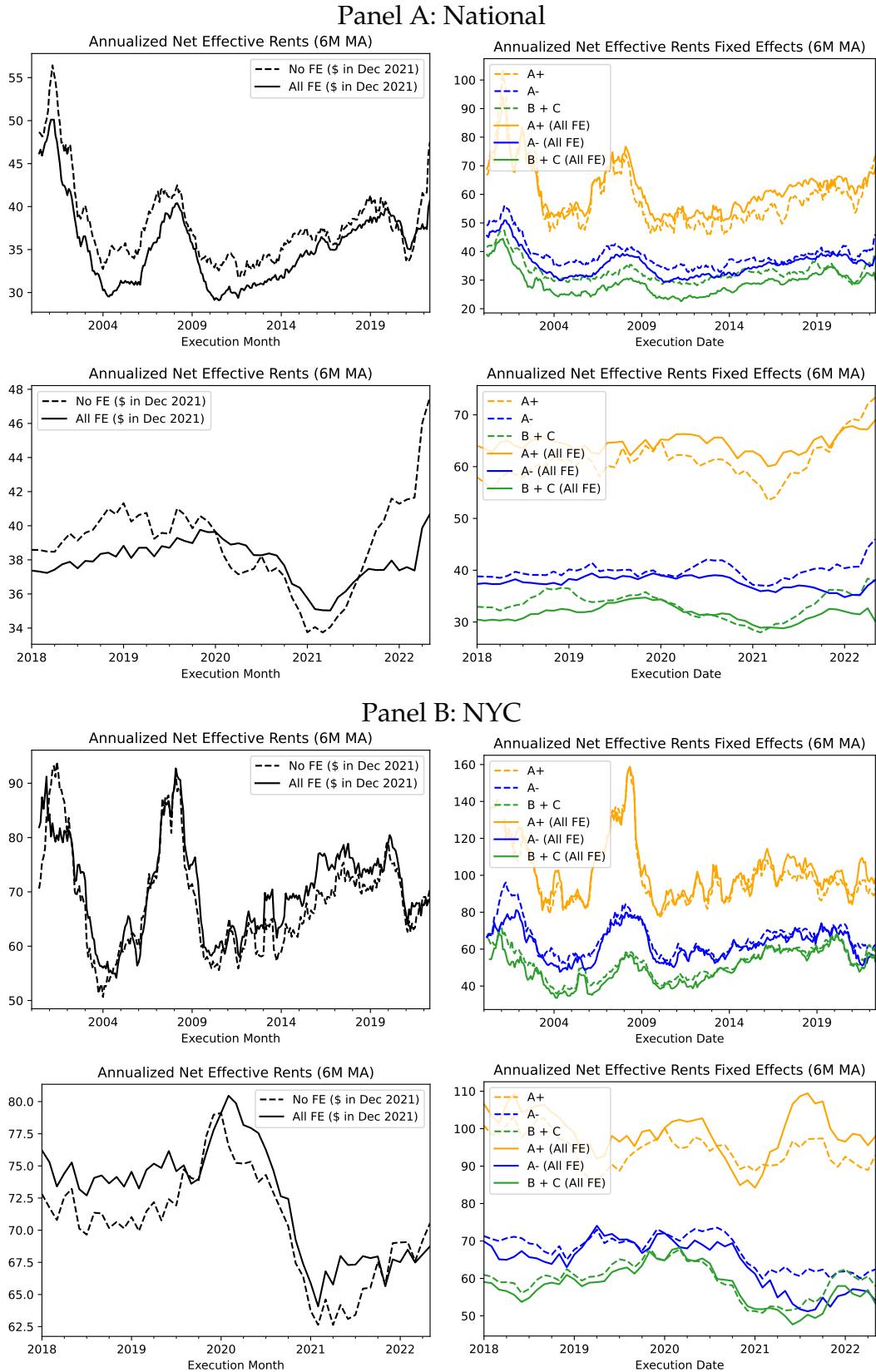
The national average NER dynamics could reflect composition effects, either in terms of in the markets in which new leases are being signed or in terms of the types of tenants signing new leases. To control for such selection effects, we remove tenant-industry and geographical fixed effects. Once fixed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

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

Flight to Quality in Building Attributes

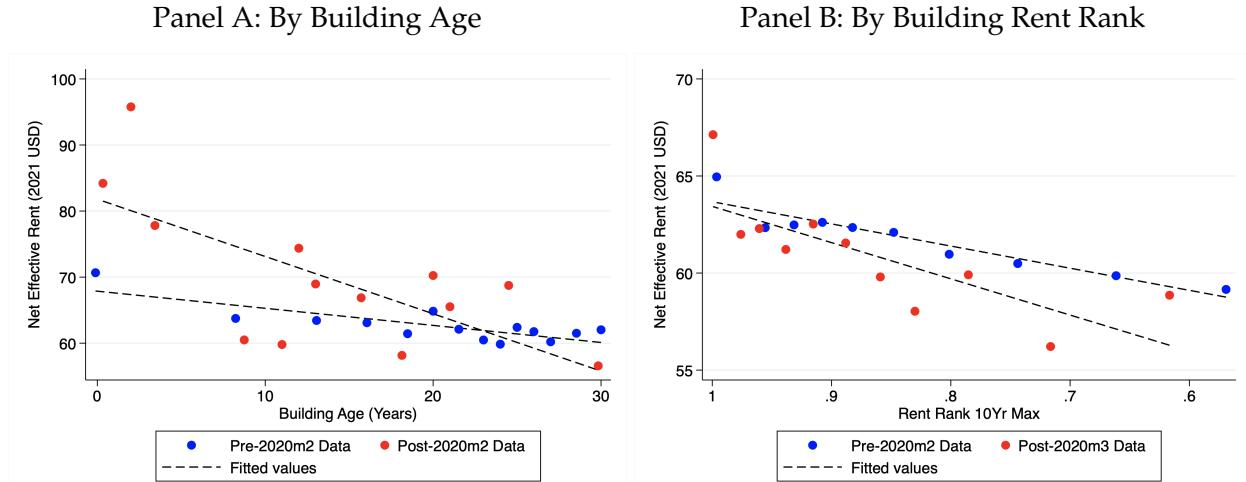
The right panels of Figure 7 break down the market-wide NER dynamics by quality segment: A+, A- (all other class A), in addition to B and C units. We focus on the solid lines, which

Figure 7: Net Effective Rent on New Leases



Source: CompStak. All FE includes state, major/non-major market, industry and renewal FEs. Major markets are defined in footnote 6.

Figure 8: Building Quality and Changes in Rents



remove fixed effects. Nationally, A+ rents on new leases show resilience, rising modestly between December 2019 and May 2022. Lower-quality office rents, by contrast, see a much steeper decline over the pandemic. In NYC, A+ rents on new leases show stronger declines in 2020, but rebound more sharply in 2021 compared to other market segments. Rents on lower-quality office buildings fall without much of a rebound in 2021.

Figure 8 illustrates the flight-to-quality dimension further by plotting the relationship between building age and NER in Panel A for New York and San Francisco leases. The NER is residualized with respect to month, submarket, and tenant fixed effects, and so as to control for shifting geographic or tenant composition. It shows that the rent-quality gradient steepens substantially for leases signed in March 2020 or later versus before. Rather than sorting buildings by age, Panel B sorts them by their rent rank, where 0.9 indicates the 90th percentile of the NER distribution. Again, we find a strong association between building quality and rents in general in the cross-section of building quality (consistent with the general role for filtering as in Baum-Snow and Rosenthal (2022)), but a steeper gradient after the pandemic. The quality attribute becomes more highly valued after the onset of the pandemic.

Table 2 provides detailed regression results of the relationship between building age and

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

Table 1: Building Quality and Rent

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Building Age (Yrs)	-0.101*** (0.015)	-0.070*** (0.011)	-0.067** (0.030)	-0.083*** (0.015)		-0.088*** (0.016)	-0.066*** (0.014)	-0.050*** (0.015)
Building Age × Post Pandemic				-0.042*** (0.013)		-0.005 (0.011)	-0.001 (0.011)	-0.127*** (0.031)
Log Building Age					-0.084*** (0.007)			
Log Building Age × Post Pandemic					-0.024*** (0.008)			
Age × Post × Major Market						-0.044*** (0.011)	-0.020** (0.009)	
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Submarket FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tenant FE	No	Yes	Yes	No	No	No	Yes	Yes
Building FE	No	No	Yes	No	No	No	No	No
Sample	Full	Full	Full	2018–2022	2018–2022	2018–2022	2018–2022	2018–2022 SF+NYC
N	374,262	207,764	196,430	93,322	93,238	93,322	37,272	8,128

standard errors in parentheses.

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

Notes: This table shows the relationship between firm quality attributes and rent gradients over the pandemic. The left hand side variable is rents in 2021 dollars, except in column (5) in which the dependent variable is log(rents). The right hand controls always include the month of lease commencement and submarket fixed effects. Additional controls include a fixed effect for tenant identity (not available for all leases), as well as a fixed effect for the building. The sample includes all years for columns (1)–(3), and subsets to leases signed from 2018–2021 for columns (4)–(8). Column (8) additionally subsets to San Francisco and New York City. To illustrate the changing premium on quality, we introduce an interaction with post pandemic from column (4), defined as the time period from March 2020 and afterwards. Major markets are defined in footnote 6. Standard errors are double clustered at the month of lease commencement and submarket level.

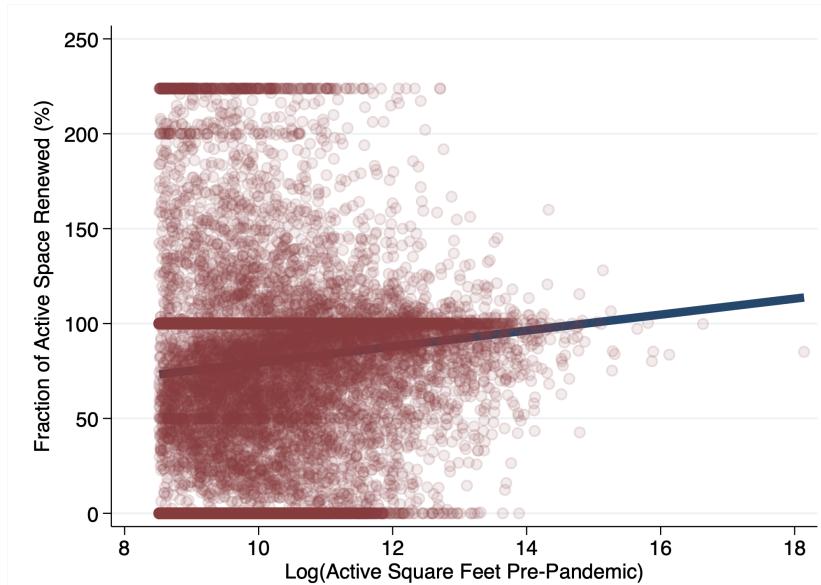
2.5 Connecting Remote Work and Office Demand

Fully Remote Workers

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

To illustrate shifting firm space demands during the pandemic, Figure 9 plots the relationship between the change in leased space between December 2019 and May 2022 by measuring the change in space at the tenant-level (y-axis) against tenant size, as measured by the log of total sf of active leases before the pandemic (x-axis). We estimate a strongly positive relationship (blue line), which suggests that the decline in tenant space demand is dominated by smaller firms. This is consistent with the idea that small firms are more likely to be financially constrained (Beck, Demirguc-Kunt and Maksimovic, 2005), and hence more sensitive to the cost of commercial leases and more likely to adopt remote work.

Figure 9: Change in Firm Office Demand and Size



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

Job Postings

In order to connect the changes in office demand over the course of the pandemic to shifts in remote work more directly, we conduct two exercises. First, we use job posting data from Ladders which allow us to measure the fraction of a firm's job listings that are for

fully-remote positions.⁷ We then estimate the relationship between the change in office demand, measured as the percentage change in active lease space in square feet normalized by employment growth since January 2020, and the fraction of job postings that are remote. Tenants will have a more negative change in office demand if they do not renew leases that come up for renewal during the pandemic, if they renew and take less space, or if they do not expand space in proportion to their total number of employees. We merge job postings and tenant data for 135 large tenants.

Table 2 reports the results. The change in office demand is measured over various periods ranging from the last 3 to the last 24 months (relative to the time of data collection in February 2022). We find a significant negative relationship at all horizons. Our results suggest that firms that express a greater remote work preference in job listings have lower demand for office space. A 10% point increase in the share of remote job postings lowers office demand by 3.9–4.9% points. This result is consistent with the idea that durable shifts in remote work are changing the demand for office space.

Hybrid Work

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

⁷The Ladders data contains a flag indicating whether the position is remote or not.

Table 2: Remote Listings and Office Demand

	(1)	(2)	(3)
	Δ Space	Δ Space	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 (-0.61)	-0.0106 (-0.52)	-0.0156 (-0.77)
Observations	135	135	135
R ²	0.042	0.044	0.030

t statistics in parentheses.

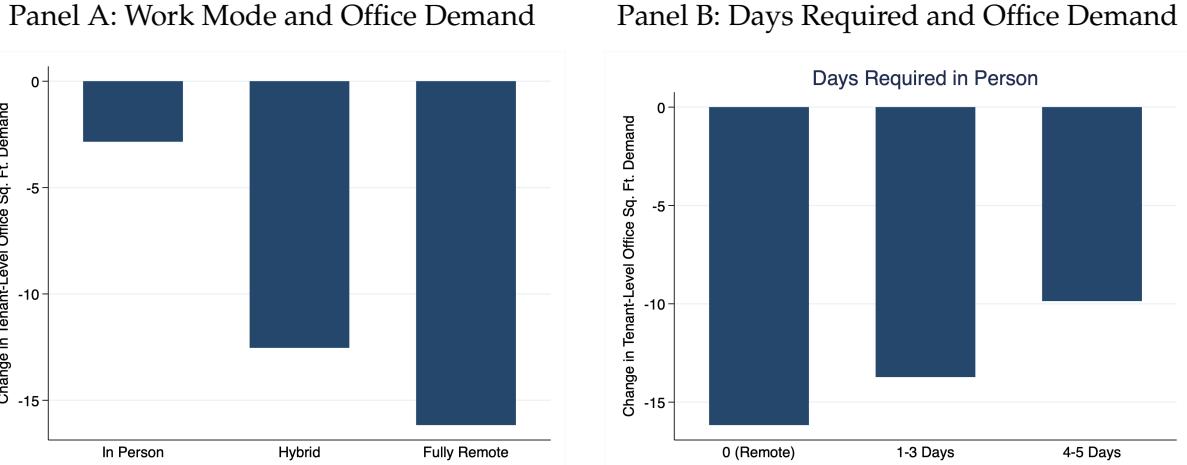
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.

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

The left panel of Figure 10 shows that hybrid work is strongly associated with lower office space demand. Firm-level office demand drops by 12.5% for hybrid firms, while firms announcing that workers must return in-person see only minimal change in space demand

Figure 10: Hybrid Work and Office Demand



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

(this decline is statistically significant in a regression). The decline in space for firms announcing a fully-remote future show the largest decline in office demand, a 16.2% decline in square footage. The latter decline is not even larger because tenants have in-place lease commitments.

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

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

3 Office Valuation Model

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

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

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

Several real-world complications arise regarding a property's cash flows which make this valuation more difficult than the valuation of, say, a stock's dividend stream. Each building is a portfolio of leases with different lease terms and maturity dates. Physically identical buildings therefore have different valuations as a result of different lease structures in place. The leases are finite, but there is additional rental revenue after the leases mature. After some initial vacancy, tenant improvements, and concessions (e.g., free rent) the space will be released at the market rent. Furthermore, the building may not be fully leased, in which case vacancy creates cash flow shortfalls. Hence, the key sources of risk are vacancy risk and market rental risk. On the cost side, the operating expenses including the reserve account to provision for regular capital expenditure or maintenance. A part of the costs is fixed, while another part is variable (with occupancy). Costs also include leasing commissions, which are different for new leases and lease renewals. Finally, there is the risk of supply growth.

The model we propose includes most of these real world features in a tractable way. It can be used to value an individual building, or a (sub-)market, which is a portfolio of buildings. The full derivation of the model is in Appendix B. This model should be useful for valuing income-generating properties in any sector or location. Section 3.3 describes the calibration of the model, which will focus on the New York City office market.

3.1 Modeling Revenues

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

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

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

The first term denotes the space that was occupied at the end of last period which is not up for renewal. The second term denotes the space that was up for renewal and is renewed for the same or for less space. Here, $0 \leq s_{t+1}^O(z') \leq 1$ is the share of office space that was up for renewal which is being renewed in period $t + 1$. This is a stochastic process whose realized value depends on the state of the world z' in period $t + 1$. It combines the extensive margin of renewal (the share of space that gets renewed versus not-renewed) and the intensive margin

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

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

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

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

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

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

with the law of motion:

$$\hat{Q}_{t+1}^O(\hat{Q}_t^O, z') = \min \left\{ \frac{\hat{Q}_t^O(1 - \chi) + \hat{Q}_t^O \chi s_{t+1}^O(z') + (1 - \hat{Q}_t^O) s_{t+1}^V(z')}{1 + \eta_{t+1}(z')}, 1 \right\}. \quad (2)$$

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

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

in which R_t^O is the average net effective rent per square foot on existing leases and R_{t+1}^m is the market's net effective rent (NER) per square foot on newly executed leases. The net effective rent incorporates concessions (free rent) and tenant improvements. We assume that

all new leases are signed at the market NER. The rent on existing leases is a geometrically-decaying weighted average of all past market rents, where the weights capture the shares of outstanding leases signed in each of the prior periods:

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

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

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

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

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

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

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

The law of motion for the scaled state variable becomes:

$$\hat{R}_{t+1}^O(\hat{R}_t^O, z') = \frac{1 - \chi}{1 + \epsilon_{t+1}(z')} \hat{R}_t^O + \chi \quad (3)$$

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

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

Define potential rent as the rent revenue based on full occupancy at the prevailing market

rent: $\bar{Q}_t R_t^m$. Denote the rent revenue scaled by last period's potential rent with a hat:

$$\begin{aligned}\widehat{Rev}_{t+1}(\widehat{Q}_t^O, \widehat{R}_t^O, z') &= \frac{Rev_{t+1}}{\bar{Q}_t R_t^m} \\ &= (1 - \chi) \widehat{Q}_t^O \widehat{R}_t^O + \left[\widehat{Q}_t^O \chi s^O(z') + (1 - \widehat{Q}_t^O) s^V(z') \right] (1 + \epsilon(z'))\end{aligned}$$

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

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

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

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

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

$$\hat{V}_t^R(\widehat{Q}_t^O, \widehat{R}_t^O, z) = \sum_{z'} \pi(z'|z) M(z'|z) \left\{ \widehat{Rev}_{t+1}(\widehat{Q}_t^O, \widehat{R}_t^O, z') + (1 + \eta(z'))(1 + \epsilon(z')) \hat{V}_{t+1}^R(\widehat{Q}_{t+1}^O, \widehat{R}_{t+1}^O, z') \right\} \quad (4)$$

subject to the laws of motion for the scaled state variables (2) and (3).

3.2 Modeling Costs

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

We fold the per-period equivalent of capital expenditures into the operating expenses, a common practice (the capital reserve account). These per-period capital expenditures are independent of building occupancy. Other operating costs that are independent of occupancy are: property insurance, property taxes, and the fixed part of utilities and maintenance. We refer to these combined fixed costs per square foot as C_t^{fix} . The presence of fixed costs acts

as operational leverage to the asset. Utilities and maintenance also contain a variable component that depends on building occupancy. Variable costs per square foot are denoted as C_t^{var} . Finally, leasing commissions (or broker fees) capture costs associated with bringing in new tenants. When a lease expires, leasing commissions are higher for new leases than for renewals: $LC^N > LC^R$. Commissions are variable costs, proportional to the first-year rental revenue from the lease.

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

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

We scale costs by lagged potential rent:

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

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

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

Note that \widehat{Cost}_{t+1} only depends on \hat{Q}_t^O and on z' , not on \hat{R}_t^O .

Recall the expected PDV of costs V_t^C :

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

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

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

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

$$\widehat{V}_t^C(\widehat{Q}_t^O, z) = \sum_{z'} \pi(z'|z) M(z'|z) \left\{ \widehat{\text{Cost}}_{t+1}(\widehat{Q}_t^O, z') + (1 + \eta(z'))(1 + \epsilon(z')) \widehat{V}_{t+1}^C(\widehat{Q}_{t+1}^O, z') \right\} \quad (5)$$

subject to the law of motion for the scaled state variable in (2).

Bellman equations (4) and (5) have closed-form solutions spelled out in Appendix B.

3.3 Calibration

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

3.3.1 States and State Transition Probabilities

The state variable z follows a Markov Chain which can take on four values: expansion (E), recession (R), WFH expansion (WFH-E), WFH recession (WFH-R). Here, WFH stands for a world where a lot of work is done remotely or in hybrid format. Before 2020, the world was oscillating between the E and R states.⁸

The model is calibrated at an annual frequency. We decompose the 4×4 annual state transition probability matrix as the Kronecker product of two 2×2 transition probabilities. The first matrix governs the dynamics between expansions and recessions. The second one governs the dynamics between no-WFH and WFH states. These two components are as

⁸We can think of the two non-WFH states as states where there was a small amount of remote work. American Time Use Survey data for 2017 put the fraction of remote work at around 5%.

sumed to be independent:

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

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

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

The WFH transition matrix is a key object in our valuation exercise. The no-WFH state captures an environment in which remote work is rare, while the WFH state captures an environment in which remote work is common. We set the probability of entering in the WFH state from the no-WFH state equal to $q = 5\%$, to capture the idea that a transition to mass adoption of remote work was unlikely before 2020. The second parameter is the probability of remaining in the WFH state conditional on having entered it, which we label p . The latter governs the persistence of remote work, and it is a key parameter of interest in the paper. We will infer the value of p from the observed change in class A+ office valuations at the onset of the pandemic, as measured from office REIT data, and perform robustness with respect to this parameter. As explained in detail below, this calibration delivers $p = 0.8176$. These two parameters pin down $\pi^{WFH}(z'|z)$:

$$\pi_{WFH} = \begin{bmatrix} \text{No WFH} & \text{WFH} \\ \text{No WFH} & \text{WFH} \end{bmatrix} = \begin{bmatrix} 1 - q & q \\ 1 - p & p \end{bmatrix} = \begin{bmatrix} 0.95 & 0.05 \\ 0.1824 & 0.8176 \end{bmatrix}$$

3.3.2 State Prices

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

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

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

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

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 conditional on each pair (z, z') . That is, we want the conditional Euler equations for the aggregate stock market return Ret^{mkt} be satisfied for each state $z = E, R$:

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

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

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

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

The SDF component $M^{WFH}(z'|z)$ governs how the risk associated with working from home is priced. It is chosen to price the returns on a portfolio of stocks that goes long

companies that benefit from remote work and short companies that are exposed to remote work. We exclude real estate stocks from the portfolio on purpose. Appendix A.2 contains the details of the WFH factor construction. We call this portfolio the WFH equity factor.

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

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

We estimate the (conditional) stock and bond betas in the December 2014–December 2019 period. Appendices A.4 and A.5 show how we pin down the (conditional) market prices of risk for the WFH equity risk factor, and for the stock and bond risk factors, respectively. Given our value of $\lambda^{wfh} = -7.0\%$, we find $Ret^{wfh}(z' = \text{no WFH}|z = \text{No WFH}) = -6.42\%$.

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

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

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

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

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

$$M^{WFH,unscaled} = \begin{matrix} & \text{No WFH} & \text{WFH} \\ \text{No WFH} & \begin{bmatrix} 1 & 1.696 \end{bmatrix}, & M^{WFH} = \begin{matrix} & \text{No WFH} & \text{WFH} \\ \text{No WFH} & \begin{bmatrix} 0.966 & 1.639 \end{bmatrix} \\ \text{WFH} & \begin{bmatrix} 0.627 & 1.080 \end{bmatrix} \end{matrix} \\ \text{WFH} & \begin{bmatrix} 1 & 1.696 \end{bmatrix} \end{matrix}$$

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

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

3.3.3 Office Cash Flows for All NYC

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

We set the lease expiration parameter at $\chi = 0.14$. This delivers a lease duration of 7.40 years, matching the CompStak average office lease term in the New York City data. Table 3 lists the remaining parameters, which vary by state.

Table 3: Calibration for All NYC

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0544	-0.1251	0.0334	-0.1699
Supply growth	η	-0.0152	-0.0158	-0.0407	-0.0413
Lease renewal share	s^O	0.8259	0.2897	0.2748	0.0964
New leasing share	s^V	0.1838	0.3350	0.0612	0.1115
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

Market NER growth ϵ in expansions and recessions comes from the January 2000 to December 2019 CompStak data.⁹ NER is strongly pro-cyclical. Market NER growth in the remote work state comes from the December 2019 to May 2022 CompStak data. Market NER growth was -16.99% from December 2019 to December 2020 (a WFH-R episode), and +3.34% per year from December 2020 to May 2022 (1.5 WFH-E years).

Supply growth $\eta(z)$ incorporates new construction net of depreciation and reductions in office space due to conversion to alternative use. The values for supply growth for expansion and recession periods are calculated from CompStak based on the year of construction of all office buildings. New construction is 1.18% in expansions and 1.12% in recessions. We subtract a 2.70% depreciation rate, a realistic number for office property, from the new construction numbers to arrive at the net supply growth η reported in the table.¹⁰ Supply growth is acyclical because of the long construction lags for office properties.

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

The parameters $s^O(E), s^O(R), s^V(E), s^V(R)$ govern office demand across the business cycle in the non-WFH states. We pin down these four parameters to match four moments of the NYC contractual vacancy rate over the period 1987.Q1–2019.Q4, plotted in panel B of Figure 3. Those moments are the mean, the standard deviation, the maximum, and the minimum. The resulting lease renewal share for existing leases that are up for renewal, s^O , is

⁹Since NBER business cycles in this period (and before) are shorter than commercial real estate (CRE) leasing cycles, we use the latter to determine the values for annual NER growth in expansions and recessions. Strict adherence to NBER dates would result in office NER growth that is far too similar across expansions and recessions, and make the large fluctuations in rent growth observed in the data highly unlikely events from the perspective of the model.

¹⁰Our depreciation estimate corresponds closely to the 39 years of allowable depreciation expense for non-residential commercial real estate assets for tax purposes.

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 in expansions. This calibration ensures that our model matches both the average vacancy rate of NYC office as well as the amplitude of the leasing cycle, which reflects cyclical tenant demand for office.

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

$$s_{z,wfh}^i = \delta \cdot s_z^i, \quad z = E, R, \quad i = O, V. \quad (6)$$

We estimate δ to best fit the dynamics of the office occupancy rate over the nine quarters from 2020.Q1–2022.Q1. Appendix C explains the details. The resulting value is $\delta = 0.33$, which indicates a large downward shift in office demand in the WFH state. This shift is consistent with the evidence on the large decline in new leasing activity, documented in Figure 5.

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

3.3.4 Office Cash Flows for A+ Properties in NYC

Next, we calibrate the model to A+ buildings of New York City. We use the leases on the subset of A+ buildings to get parameter estimates for the A+ NYC office sector. The calibration approach parallels that for All NYC, and is detailed in Appendix C. χ is set to be 0.14 to match the slightly higher average lease duration of 8.20 years of A+ leases in NYC. Table 4 lists the remaining parameter estimates for the A+ universe. The cost parameters are assumed to be the same as for the market as a whole.

Table 4: Calibration for NYC A+

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0482	-0.1212	0.0272	-0.0472
Supply growth	η	-0.0155	-0.0081	-0.0410	-0.0336
Lease renewal share	s^O	0.8432	0.5668	0.5361	0.3604
New leasing share	s^V	0.1160	0.1893	0.0738	0.1204

3.4 Identifying the Persistence of Work From Home

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

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

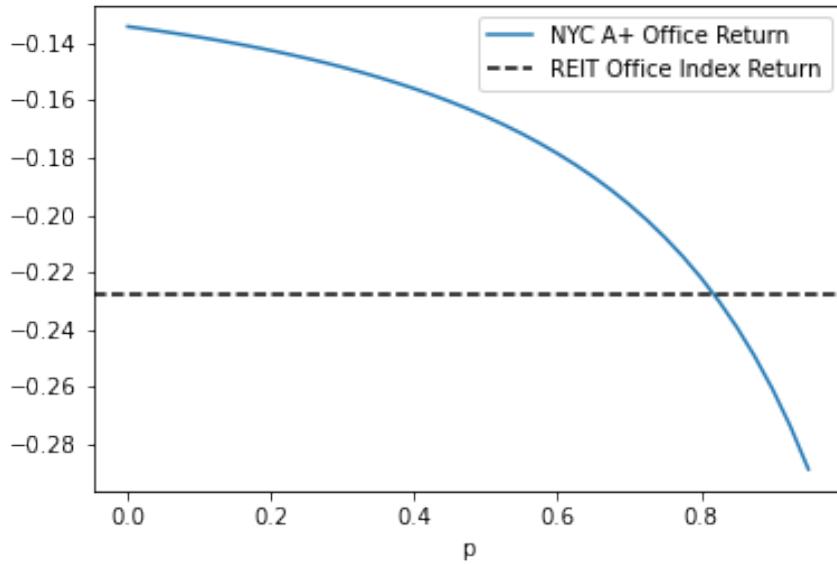
Figure 11 plots this model-implied realized return on A+ office in this transition, the left-hand side of the equation above, for a range of values of \mathbf{p} .¹¹ Since the office return in this transition varies strongly with \mathbf{p} , this moment is well-suited to identify this parameter.

In order to pick the relevant point on this curve, we turn to the REIT data. REITS invest in class A+ office properties. The three NYC-centric office REITs, (SL Green, Vornado, and Empire State Realty Trust), experienced a value-weighted return of -36.16% between December 2019 and December 2020. After unlevering this equity return, the asset return was -22.75%.¹² The model matches this decline for a value of $\mathbf{p} = 0.82$. With this key parameter identified, we can return to the calibration for the full NYC office market and calculate the

¹¹As the equation shows, this return depends also on the state pair $(\widehat{Q}_t^O, \widehat{R}_t^O)$ for 2019 and 2020, respectively. We obtain these by feeding in the sequence of annual aggregate shocks (expansions and recessions) from 1926 to 2019 obtained from the NBER recession chronology into the laws of motion of the states under the A+ calibration, which gives the 2019 values. For the 2020 values, we apply the law of motion for the state variables once more, assuming that the state transitioned from E to WFH-R.

¹²Unlevering is done based on leverage ratio and cost of debt data from NAREIT.

Figure 11: Determining p by Matching Realized Return of A+ Market



change in its value due to remote work.¹³

4 Office Valuation Results

4.1 Key Model Outcomes

Table 5 presents the model solution for the “All NYC” office calibration. The model delivers a reasonable unconditional average cap rate of 7.74% for the overall NYC office market. The cap rate is 9.73% in recessions and 7.45% in expansions.¹⁴

¹³We chose to calibrate to the full-year 2020 REIT return since the model is annual. Alternatively, one could use this calibration strategy to calibrate to the REIT return measured over at different periods. The observed office REIT returns were more negative when measured over a shorter period from February 2020–April 2020, and also when measured over the longer period from December 2019–May 2022. This makes our results conservative. One could also use our procedure to update the implied persistence parameter over time.

¹⁴The hedonic-adjusted cap rate for Manhattan Office averaged 5.3% over the period 2001–19 (Real Capital Analytics data), and model predicts 5.0% average cap rate for the same period. Cap rates were higher before 2001. Longer, national data from CBRE put the average office cap rate at 8%. Since our model’s steady state pertains to a longer period than 2001–19, the higher average is a good feature. Also, our data pertains to more than Manhattan. Cap rates are higher in the other boroughs than in Manhattan. RCA has no office cap rates for the outer boroughs. Finally, our cap rate pertains to the entire office stock and removes depreciation, which lowers the growth rate and increases the cap rate by 2.7% points. The model-implied cap rate on a building where cash-flow growth is not reduced by depreciation is therefore 5.0% rather than 7.7%. The RCA data also indicate higher cap rates in recessions (6.0% in 2001, 2008, 2009) than in expansions (5.2% for 2002–2007 and

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 7.70% and an office risk premium of 6.21%. This is naturally lower than the equity risk premium of 8.06% since an unlevered office property is less risky than the aggregate stock market (which is a levered investment). The office risk premium is substantially higher in recessions (10.16%) than in expansions (5.19%).

Table 5: Model Solution for NYC All Calibration

Statistic	Uncond	E	R	WFHE	WFHR
R_f	0.0149	0.0084	0.0467	0.0084	0.0467
Equity $\mathbb{E}[Ret] - 1$	0.0955	0.0773	0.1846	0.0746	0.1815
Equity RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0806	0.0690	0.1379	0.0662	0.1348
Cap rate	0.0774	0.0745	0.0973	0.0676	0.0999
Office $\mathbb{E}[Ret] - 1$	0.0770	0.0603	0.1484	0.0684	0.1455
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0621	0.0519	0.1016	0.0600	0.0987
$\mathbb{E}[g_t]$	-0.0007	-0.0186	0.1256	-0.0565	0.1102
Vacancy rate = $1 - \widehat{Q}^O$	0.1500	0.1053	0.1600	0.2768	0.2865
$\widehat{\text{Rev}}$	0.7876	0.7995	0.9067	0.6479	0.8087
$\widehat{\text{Cost}}$	0.4138	0.4259	0.4141	0.3777	0.3755
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.3738	0.3735	0.4926	0.2702	0.4331
\widehat{V}^R	8.4713	8.9948	8.1383	7.1768	6.7796
\widehat{V}^C	3.7269	4.0427	3.1483	3.2731	2.5389
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	4.7444	4.9521	4.9901	3.9037	4.2407

Expected NOI growth is close to zero (-0.07% per year) unconditionally. This number is in real terms and already incorporates that the office stock depreciates at 2.70% per year (so it is 2.63% before depreciation). Expected cash flow growth is higher in recessions than in expansions since recession states imply a high likelihood of transitioning to a better economic state going forward. The opposite is true of *realized* NOI growth rates in a transition from expansions to recessions, which are negative in the model (not reported).

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

The last part of the table shows the value of the building, scaled by potential rent, and broken down into the PDV of revenues minus PDV of costs. The typical NYC office trades for a multiple of 4.74 times potential gross rent unconditionally according to our calibration. The average valuation ratio of office properties in the no-WFH expansion state of 4.95 is 16.78% higher than the value of 4.24 in the WFH-R state. Appendix Figure 22 shows the valuation ratio for office \hat{V} conditional on expansion, recession, WFH-expansion and WFH-recession for NYC.

4.2 The Effect of WFH on Office Values

4.2.1 Entire Office Stock

To assess the effect of remote work on office values, we let the economy undergo the same transition as the one we considered for A+ office when calibrating the parameter p , namely from an expansion in the no-WFH state in 2019 to a WFH-R state in 2020. We feed in the observed history of expansions and recessions from 1926-2019 to arrive at the value for the endogenous state variables $(\hat{Q}_{19}^O, \hat{R}_{19}^O)$ using the laws of motion for the states (2) and (3) under the “All NYC” calibration. The model captures the decade-long expansion before the Covid-19 pandemic. We then apply the law of motion once more to obtain $(\hat{Q}_{20}^O, \hat{R}_{20}^O)$ assuming the economy transitioned from E to WFH-R between 2019 and 2020.

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

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

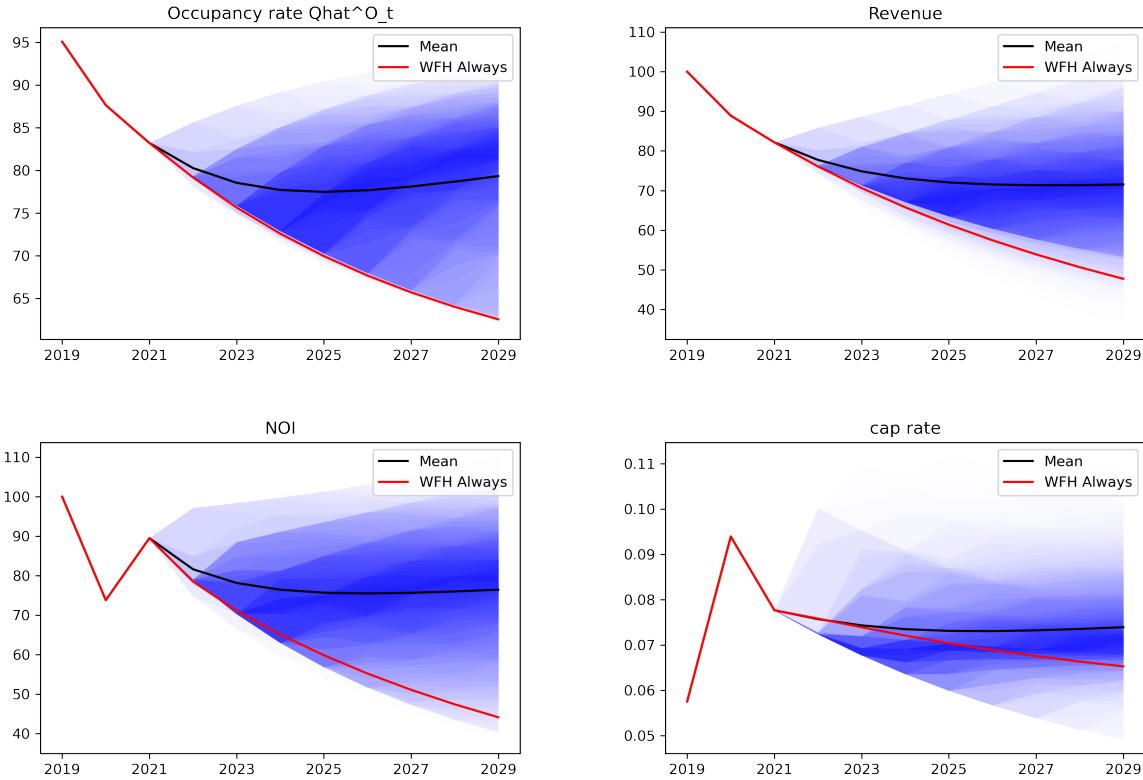
Put differently, if the entire office stock of NYC had been publicly listed, its value would have fallen by 44.80% in 2020. This same decline was 27.13% for the A+ office sector, illustrating the relative safety of A+ office.

To understand the longer-run consequences of remote work, we conduct the following simulation exercise. In the first period of the transition, from 2019 to 2020, the economy goes from the E to the WFH-R state. In the second year, from 2020 to 2021, the economy transitions from WFH-R to WFH-E. After 2021 (from 2022 onward), we let the economy evolve stochastically according to its laws of motion governed by π . Since there are many possible paths for the evolution of the state, Figures 12 and 13 show fan charts where darker blue colors indicate more likely future paths for the economy. The solid line indicates the mean path. The red line plots the average path conditional on the economy remaining in the WFH state every year until 2029. The probability of this event occurring is 19.97% according to the model.

The top left panel of Figure 12 shows the occupancy rate dynamics from the model simulation. The model captures a substantial decline in occupancy from a high value of 95.08% in 2019 to an average value of 80% in 2022. Hence the model essentially matches the observed occupancy rate, which was 78.5% in 2022.Q2. Since long-term leases continue to roll off and renew at low rates as long as the economy is in the WFH state, the decline in occupancy is protracted. Should the economy remain in the WFH state until 2029, occupancy would eventually fall below 65% even after accounting for the supply response.¹⁵ 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 17.46% between 2019 and 2021, which is close to the observed decline in active lease revenues in the CompStak data for New York City of 16.06% between December 2019 and May 2022. Lease revenues go down 28.47% by 2029 along the average path. Total lease revenue falls by much more for the red line, reflecting additionally the faster reduction

¹⁵Recall that supply growth in the WFH state is 2.55% points lower per year in the WFH than in the no-WFH states. This captures reduced construction as well as conversion of office to alternative use.

Figure 12: Key Moments Distributions, Normalized to 100 in Dec 2019



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

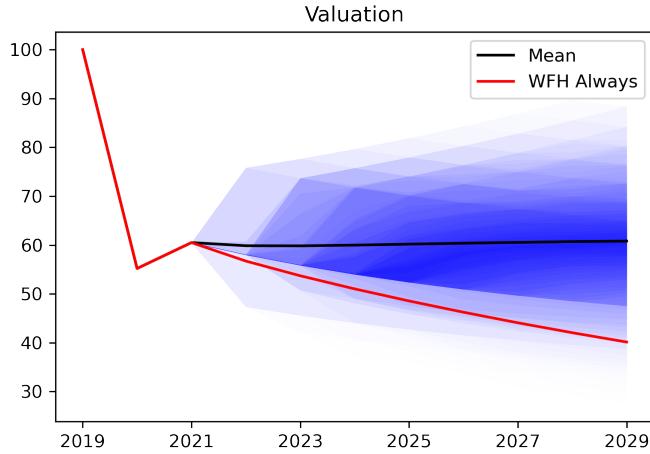
in the overall quantity of office floor space.

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

The combination of declining cash flows and rising cap rates results in a substantial change in the value of office V_t , shown in Figure 13. The graph illustrates a mean path that sees no recovery. Remote work is a near-permanent shock. Ten years after the transition, office values remain at levels that are 39.18% below the valuation in 2019. Along some sample paths, the economy returns to the no-WFH state and sees increases in occupancy rates (\hat{Q}^O), rent revenues, and NOI. Along other sample paths, the economy remains in the

WFH state (WFH-E or WFH-R) for a long period, and office valuations continue to fall. For example, conditioning on remaining in the WFH state for at least 10 years (red line), office valuation are 59.86% lower in 2029 than in 2019.

Figure 13: Office Valuation Distribution for NYC, Normalized to 100 in Dec 2019



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

A second key message from the valuation exercise is that there is substantial uncertainty around the mean path. This uncertainty is driven both by the future state of the economy: the medium-frequency fluctuations between recession and expansion as well as by the lower-frequency uncertainty about the future evolution of remote work. Office valuations are subject to *WFH risk*.

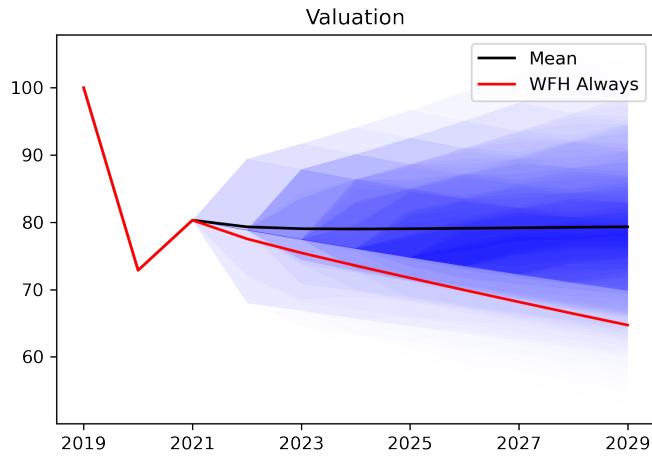
4.2.2 Flight To Quality

The previous results referred to the entire NYC office stock. We now redo the simulations for the A+ segment, which has its own cash-flow parameters. We define the A+ as in Section 2.¹⁶ The results for cap rates, valuation ratios, and vacancy rates in the A+ office segment are reported in Appendix D. They show lower cap rates and lower expected returns in the A+ segment, consistent with the lower risk of this segment.

¹⁶Buildings which contain an expensive lease—defined as higher than the 90th percentile NER for the quarter and submarket—enter the A+ segment, and remain there for ten years.

Figure 14 revisits the transition graph for office values. It shows substantially smaller value reductions both in the short- and in the long-run. The mean path has office values down by 20.67% in 2029 compared to 2019. In the scenario where the economy remains in the WFH state until at least 2029, the decline in A+ office values is 35.28%. The better performance is due to the stronger rent growth for A+ in the WFH states, and a lower risk premium for A+ office especially in the WFH state. On the flip side, the performance of the complement of A+, A-/B/C-class office is strictly worse than the overall market. Its initial value decline is -68.98% compared to -44.80% for all office.

Figure 14: Office Valuation Distribution for NYC A+, Normalized to 100 in Dec 2019



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

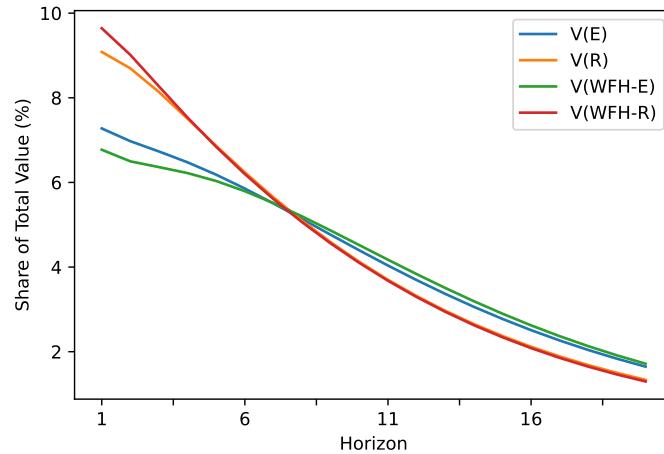
4.2.3 Term Structure of Valuations

We can decompose the (change in) office value into the contribution from each of the future cash flows. Appendix B.4 explains the procedure. Figure 15 plots the share of the total value of office that comes from each of the first 20 years of cash flows. The lines are downward sloping as cash flows in the near term are more valuable than cash flows farther in the future due to discounting. Each line refers to a different current state for the economy. Interestingly, in expansions (such as 2019) the contribution of the nearest-term cash flows is much smaller

than in the WFH-R state (such as 2020). For the share of short-term in total cash flows to rise (in present-value) between 2019 and 2020, the value of the cash flows in the farther future must falls by more than in the near future. This occurs because rents (and NOI) in the short-term are largely locked in given the long-term nature of leases. Investors would be willing to pay a premium for buildings that have a lot of long-term pre-pandemic leases in place.

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

Figure 15: Decomposing Office Values by Horizon

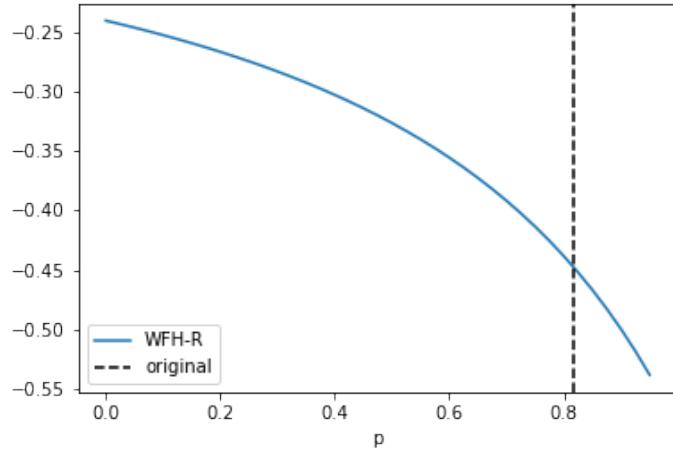


4.2.4 Robustness to Persistence of Remote Work

To assess how sensitive our headline value reduction number is, we explore alternative values for the key parameter p . Figure 16 plots the difference in office values (V) between the model with no remote work in December 2019 and the model with remote work in Decem-

ber 2020. The vertical dashed line indicates our benchmark model with $p = 0.82$, which produces a 44.80% valuation decline in the transition. This same decline is around 30.31% for a value of p that is half as large as our benchmark.

Figure 16: Change in Valuation with Different p for All NYC

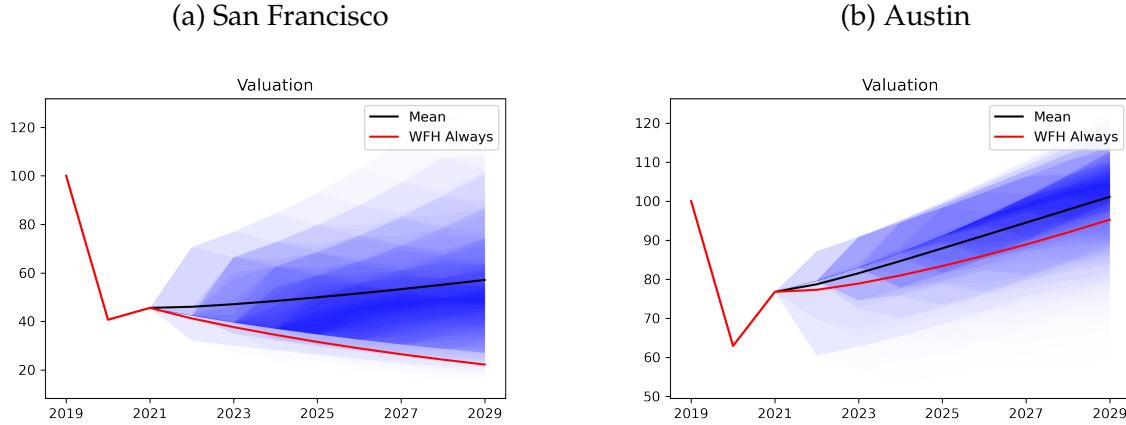


4.3 Other Office markets and Aggregate Impact

4.3.1 San Francisco and Austin

Appendix E repeats the calibration exercise for San Francisco (SF) and Austin and reports the resulting valuation moments. Figure 17 below shows the main fan chart for the valuation of the stock of SF office (left panel) and Austin office (right panel). The short-run (long-run) declines in office values are 54.43% (42.94%) for SF and 23.19% (-1.12%) for Austin. The former are larger than for NYC, due to the more cyclical nature of the SF office sector and its larger WFH exposure. This is possibly driven by SF's larger exposure to tenants from the technology sector who have embraced remote work. Austin's valuation effects are smaller than NYC due to its milder office cycles and smaller exposure to the WFH shock. Adjusted for market coverage, the total office value destruction is \$19.53 billion in SF ten years from now, while Austin does not have long-term value destruction.

Figure 17: Office Valuation Distribution, Normalized to 100 in Dec 2019



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

4.3.2 Aggregate Impact

Table 6 compiles statistics on the top-20 U.S. office markets. It reports the quantity of active leases (in sf) in December 2019 (column 1), the percent change in active lease revenue between December 2019 and May 2022 (column 2), and the change in the quantity (column 3) and NER (column 4) of newly-signed leases over the same period. These statistics are based on the CompStak data and show that the decline in leasing activity is widespread. NYC is not an outlier. The first two rows in the bottom panel compare the top-20 office markets to all 105 office markets in the data, and again show similar changes.

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

Table 6: Cross-Sectional Results For Top 20 Markets

State	Market	(1) Active SF (mi)	(2) Lease Rev Chg	(3) New SF Chg	(4) NER Chg	(5) Value Chg	(6) Coverage (%)	(7) Value Chg Scaled
NY	New York	287.36	-16.06	-53.94	-10.21	-47.52	73.58	-64.58
CA	San Francisco	61.25	-15.40	-69.26	-16.24	-14.61	62.14	-23.51
TX	Austin	26.60	-10.49	-89.05	5.17	-2.22	54.54	-4.07
DC	Washington DC	94.57	-23.52	-75.94	-12.67	-12.88	98.81	-13.03
CA	Los Angeles	74.32	-23.92	-86.21	-24.85	-9.44	42.83	-22.04
MA	Boston	55.51	-13.66	-76.63	-12.78	-7.07	35.33	-20.01
IL	Chicago	84.41	-15.81	-88.39	-5.21	-4.87	43.25	-11.26
TX	Dallas	47.54	-15.87	-85.21	3.40	-3.14	26.60	-11.80
CA	Orange County	38.47	-22.03	-60.55	-6.62	-3.27	47.36	-6.90
CA	San Diego	29.86	-15.95	-78.89	-15.58	-2.84	42.11	-6.74
VA	Arlington	26.99	-26.96	-85.91	-4.51	-3.29	36.10	-9.11
GA	Atlanta	37.25	-11.48	-84.11	-19.45	-2.47	31.33	-7.88
TX	Houston	42.11	-25.51	-58.87	-24.70	-3.20	28.63	-11.18
CA	San Jose	22.33	-16.45	-83.69	-13.55	-2.54	11.39	-22.30
CA	Palo Alto & Sunnyvale	13.93	5.33	18.38	-6.59	-1.33	36.10	-3.68
CO	Denver	29.82	-18.53	-79.08	-14.55	-1.97	29.78	-6.62
PA	Philadelphia	26.86	-20.08	-77.84	5.37	-1.88	23.24	-8.09
NC	Charlotte	22.98	-1.99	-82.65	-6.29	-1.18	47.54	-2.48
NJ	North Jersey	16.61	-11.36	-71.84	7.60	-1.33	18.29	-7.27
CA	Oakland	8.76	0.54	-80.66	-13.54	-0.76	9.01	-8.43
Top 20 (Compstak)		1047.56	-16.76	-71.86	-5.26	-127.82	41.26	-271.02
Other markets (Compstak)		772.17	-17.21	-81.92	7.99	-51.73	36.10	-143.31
U.S. (Compstak)		1819.73	-16.89	-76.59	2.45	-179.55	38.87	-414.33

Notes: The table reports the quantity of active leases pre-pandemic (in million sf), the change in active leasing revenue (in % of pre-pandemic leasing revenue), the change in newly signed leases (% of pre-pandemic newly signed sf), the change in the net effective rent per sf on newly-signed leases (in % of pre-pandemic market NER), and the change in valuation (in 2021 December dollars) for top 20 markets and for all 105 markets in CompStak combined (last two rows). Pre-pandemic active space in column (1) is calculated in December 2019. The changes in columns (2)-(4) are measured between December 2019 and May 2022. The value change in column (5) measures the change in the total value of office in dollars between the end of 2019 and the end of 2021. It combines the change in the value-to-revenue ratio over the first two years of the pandemic from the model calibration with the size of the market in column (1) and the drop in leasing revenue in column (2). The value changes for New York, San Francisco, and Austin in the top panel are based on full calibrations of the model to each of these cities separately, while the change in the valuation-to-revenue ratio for the other 17 top-20 markets in the middle panel is based on the change in the valuation ratio from the New York City calibration. The aggregate numbers in columns (4) for the top-20 market and national NER changes are adjusted by submarket FEs to remove composition effects. Column (6) is the CompStak coverage ratio, measured as the ratio of pre-pandemic active leased space in CompStak and active leased space in Cushman & Wakefield data. Column (7) divides column (5) by the coverage ratio in column (6).

markets, we obtain a \$127.8 billion value loss. Extending the analysis to the remaining 85 office markets, we find an additional \$51.7 billion in value destruction for a total of \$179.6 billion across all 105 markets in the Compstak data.

CompStak does not provide universal coverage. Based on Cushman and Wakefield reports, we are able to obtain a December 2019 coverage ratio estimate for 18 of the top-20 markets, shown in column (6). A coverage ratio of 36.1% for the remaining 87 markets (=105-18) reconciles the total U.S. office inventory in CompStak to that in Cushman & Wakefield. To obtain our aggregate value impact statistic in column (7), we divide column (5) by column (6). We arrive at an aggregate \$414.3 billion loss in office values nationwide over the 2019–2021 period. This number is close to the aggregate impact numbers reported in the introduction, which pertained to the short-run (2019–2020) and long-run (2019–2029) changes

and used the same scaling-up procedure.

5 Discussion and Conclusion

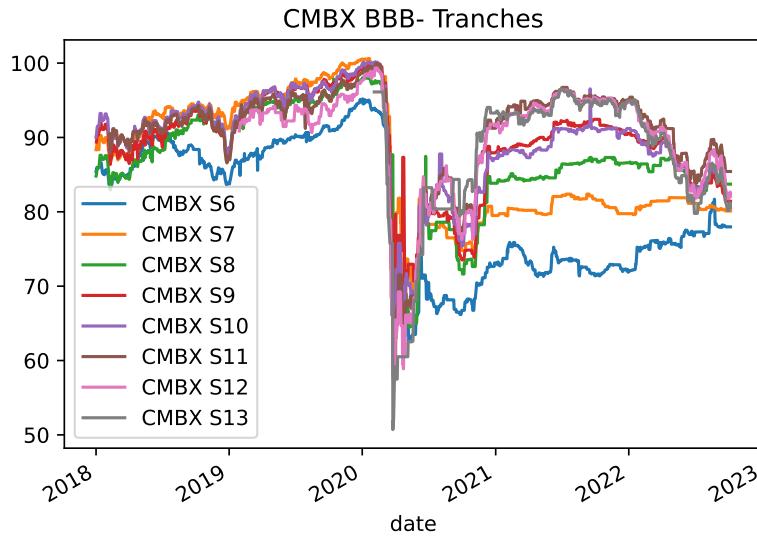
The real estate sector provides a unique vantage point to study the large social shifts in the wake of the Covid-19 pandemic. We estimate a 44.80% decline in the value of New York City’s office stock at the outset of the pandemic. We estimate that remote work is likely to persist and result in long-run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

These valuation changes are large, but since about 80% of the office stock is privately-held and private transactions have been few and far between (and represent a heavily selected sample), it has been difficult to directly observe the valuation changes in the market place. One exception is office REIT stocks, whose (unlevered) valuations the model matches both in 2020 and in 2022. Other market indicators that have turned bearish are short interest (as a share of equity float) in office REIT stocks and the prices of CMBX tranches rated BBB–. Specifically, tranches in more recent CMBX vintages, which have a larger share of office collateral than earlier vintages, have experienced larger price declines (Figure 18).

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

Trends in office occupancy have prompted discussion on the merits of conversion of office, either from A-/B/C to A+ office or to alternative use such as multi-family. The former conversion could make sense in light of the flight to quality and the likely dearth of new office construction for years to come. The latter conversion makes sense in light of the lack of

Figure 18: Price of CMBX Insurance



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

affordable housing in large cities, but often runs into issues relating to the structural feasibility, zoning restrictions, and return on investment. Older buildings tend to be more amenable to apartment conversion. Whether and how these conversions take place will have an important impact on urban design. Given the negative externalities associated with office vacancy, there may be a role for local governments to subsidize the conversion.

Finally, the decline in office values and the surrounding CBD retail properties, whose lease revenues have been hit at least as hard as office, has important implications for local public finances. For example, the share of real estate taxes in NYC's budget was 53% in 2020, 24% of which comes from office and retail property taxes.¹⁷ Given budget balance requirements, the fiscal hole left by declining CBD office and retail tax revenues would need to be plugged by raising tax rates or cutting government spending. Both would affect the attractiveness of the city as a place of residence and work. These dynamics risk activating a fiscal doom loop. With more people being able to separate the location of work and home,

¹⁷ An additional 3% of tax revenue comes from a tax on real estate tenants.

the migration elasticity to local tax rates and amenities may be larger than in the past. Future research should explore these implications and study the role for federal fiscal policy.

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Internet Appendix

A Asset Pricing Model to Infer Expected Returns

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

A.1 Model for Expected Returns

We propose the following model for the expected log return on office REITS r_t^o :

$$x_t \equiv \mathbb{E}_t[r_{t+1}^o] = r_t^f + \beta_t^m \lambda^m + \beta_t^b \lambda^b + \beta_t^{wfh} \lambda^{wfh} \quad (7)$$

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

A.2 Constructing a WFH Equity Risk Factor

We form a portfolio (Working from Home Index) that goes long stocks which benefit from remote work, and short stocks which suffer from the move to working-from-home. This entails long positions in the technology sector, health care sector, and pharmaceutical companies developing vaccine candidates and short positions in the transportation sector, entertainment sector, and hotel sector. The WFH index composition can be found in Table 7. Several variations on the factor construction, such as excluding entertainment stocks or just going long technology stocks and short transportation stocks, give similar results.

The WFH risk factor is a monthly rebalanced, long-short market capitalization weighted basket of stocks. On the last working day r of each month, which we call the rebalance day,

each stock i in the long leg is assigned a weight $w_{i,l,r}$ and each stock j in the short leg is assigned a weight $w_{j,s,r}$

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

Where $S_{k,r-1}$ is the market capitalization of stock k on day $r-1$, the working day immediately preceding rebalance day r , and $c_{l,r}$ and $c_{s,r}$ are the constituents in long and short legs respectively for rebalance date r . Further, we impose weight caps of 10% on each stock in the long leg and 20% on each stock in the short leg. The remaining weights are redistributed among remaining stocks of that leg in the same proportion above, i.e. proportional to their market capitalization, such that:

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

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

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

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

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

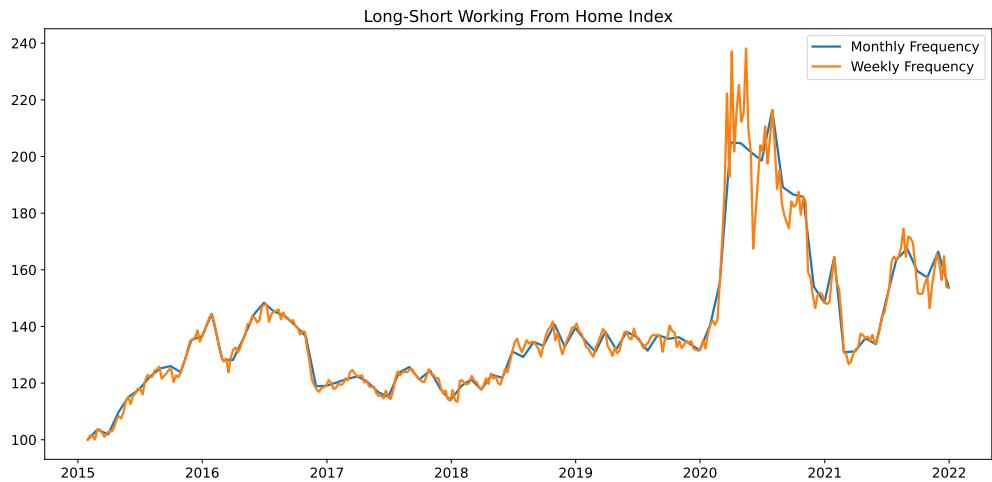
$$R_t = R_{l,t} - R_{s,t}$$

The level of the Working from home index on date t , WFH_t is then given by:

$$WFH_t = WFH_{t-1}(1 + R_t); WFH_0 = 100$$

We start the WFH time series in 2015 since the composition of the WFH index is relatively stable after that date. Prior to 2015, many of the companies in the long or short leg were not trading, such as Zoom. Several perturbations on the WFH index construction deliver similar results. Figure 19 plots the WFH index constructed from weekly and monthly returns. Below we use the monthly return series. The figure cumulates the WFH index returns starting from 100 at the start of 2015.

Figure 19: Working From Home Risk Factor



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

Table 7: Composition of WFH Index

Panel A: Long Positions

Ticker	Name	Leg	Sector
PFE	Pfizer Inc	Long	Vaccine Candidates
MRNA	Moderna Inc	Long	Vaccine Candidates
BNTX	Biontech Se	Long	Vaccine Candidates
JNJ	Johnson & Johnson	Long	Vaccine Candidates
AZN	Astrazeneca Plc	Long	Vaccine Candidates
NVAX	Novavax Inc	Long	Vaccine Candidates
REGN	Regeneron Pharmaceuticals	Long	Healthcare/Biopharma
GILD	Gilead Sciences Inc	Long	Healthcare/Biopharma
SRNE	Sorrento Therapeutics Inc	Long	Healthcare/Biopharma
AMGN	Amgen Inc	Long	Healthcare/Biopharma
NFLX	Netflix Inc	Long	Information Technology
GOOGL	Alphabet Inc	Long	Information Technology
FB	Meta Platforms Inc	Long	Information Technology
AMZN	Amazon.Com Inc	Long	Information Technology
MSFT	Microsoft Corp	Long	Information Technology
CTXS	Citrix Systems Inc	Long	Information Technology
PRGS	Progress Software Corp	Long	Information Technology
TEAM	Atlassian Corporation Inc	Long	Information Technology
NTNX	Nutanix Inc	Long	Information Technology
ZM	Zoom Video Communications	Long	Communication
VZ	Verizon Communications Inc	Long	Communication
ATVI	Activision Blizzard Inc	Long	Communication
NTDOF	Nintendo Ltd	Long	Communication
EA	Electronic Arts Inc	Long	Communication
CSCO	Cisco Systems Inc	Long	Communication
MTCH	Match Group Inc	Long	Communication
EGHT	8X8 Inc	Long	Communication
VG	Vg Corp	Long	Communication
PANW	Palo Alto Networks Inc	Long	Communication
PTON	Peloton Interactive Inc	Long	Virtual Healthcare
TDOC	Teladoc Health Inc	Long	Virtual Healthcare
VMW	Vmware Inc	Long	Cloud Technologies
INSG	Inseeog Inc	Long	Cloud Technologies
ZS	Zscalar Inc	Long	Cloud Technologies
DBX	Dropbox	Long	Cloud Technologies
NTAP	Netapp Inc	Long	Cloud Technologies
OKTA	Okta Corp	Long	Cybersecurity
FTNT	Fortinet Inc	Long	Cybersecurity
DOCU	Docusign	Long	Online Document Mgmt
BOX	Box Inc	Long	Online Document Mgmt
UPLD	Upland Software Inc	Long	Online Document Mgmt

Panel B: Short Positions

DAL	Delta Air Lines Inc	Short	Transporation
UAL	United Airlines Holdings Inc	Short	Transporation
AAL	American Airlines Group Inc	Short	Transporation
LUV	Southwest Airlines Co	Short	Transporation
CCL	Carnival Corp	Short	Transporation
NCLH	Norwegian Cruise Line Holdin	Short	Transporation
UNP	Union Pacific Corp	Short	Transporation
HLT	Hilton Worldwide Holdings In	Short	Hotels
MAR	Marriott International	Short	Hotels
H	Hyatt Hotels Corp	Short	Hotels
IHG	Intercontinental Hotels	Short	Hotels
SIX	Six Flags Entertainment Corp	Short	Entertainment
EB	Eventbrite Inc	Short	Entertainment
LYV	Live Nation Entertainment In	Short	Entertainment
WYNN	Wynn Resorts Ltd	Short	Entertainment
LVS	Las Vegas Sands Corp	Short	Entertainment
CZR	Caesars Entertainment Inc	Short	Entertainment

A.3 WFH Risk Exposure

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

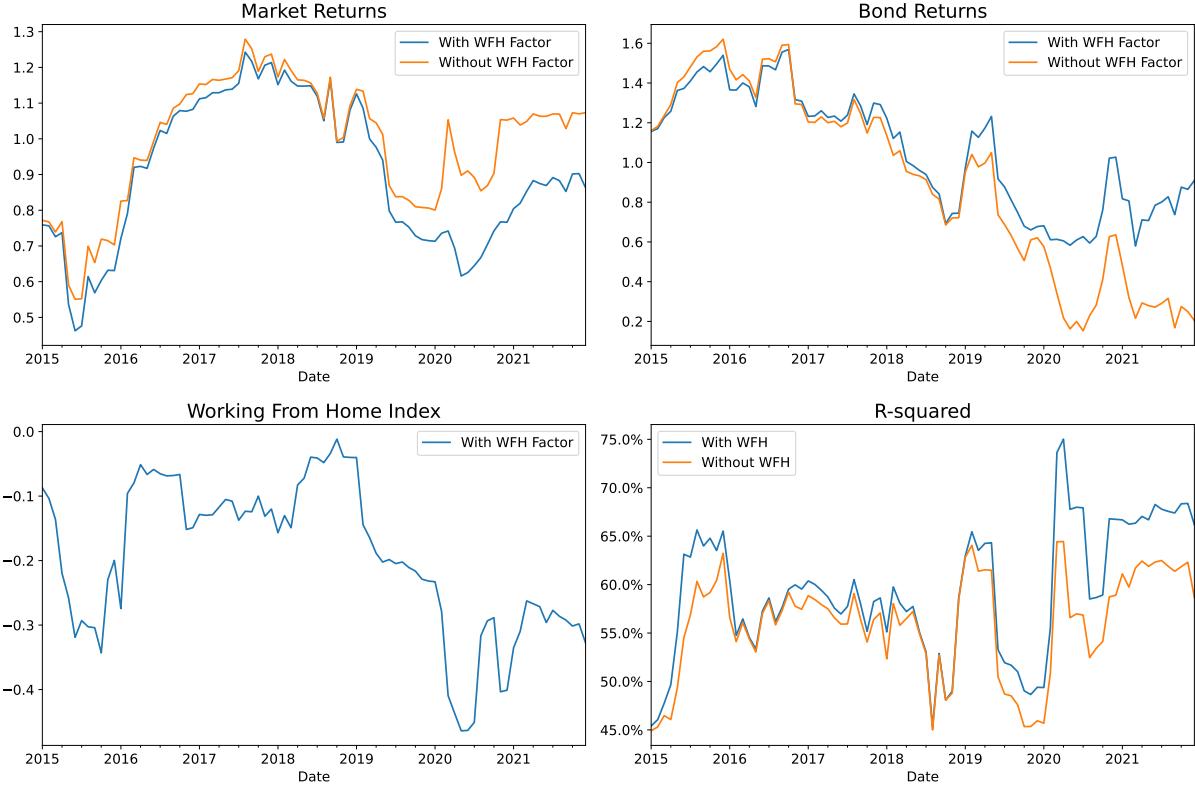
$$r_{t+1}^o - r_t^f = \alpha + \beta_t^m(r_{t+1}^m - r_t^f) + \beta_t^b(r_{t+1}^b - r_t^f) + \beta_t^{wfh}r_{t+1}^{wfh} + e_{t+1} \quad (8)$$

Figure 20 shows the estimated betas for office REITS. The patterns in the stock and bond betas of office REITS in the three-factor model (blue line) are similar to those in the two-factor model without the WFH factor (orange line) before the pandemic. However, omission of the WFH factor leads one to overstate the stock market beta during the pandemic (top left panel). The reverse is true for the bond beta in the top right panel.

The WFH beta in the bottom left panel is close to zero prior to the pandemic in February 2020, an exposure estimated over the 36-month window from March 2018 through February 2020. The β^{wfh} for Office REITS then starts a precipitous decline to around -0.5. It remains strongly negative until the end of our sample in December 2021, ending at -0.3 in December

2021. The bottom-right panel shows that the R^2 improved during the pandemic due to the inclusion of the WFH factor.

Figure 20: Risk Exposures of Office REITs During Covid with WFH



A.4 WFH Risk Price

We estimate the market prices of risk on the WFH factor, λ^{wfh} , using the cross-section of 22 individual office REITs listed in Table 8.

Table 8: List of Office REITS

Office REIT	Ticker
Alexandria Real Estate Equities, Inc.	ARE
Brandywine Realty Trust	BDN
Boston Properties, Inc.	BXP
CIM Commercial Trust Corp	CMCT
Cousins Properties	CUZ
Columbia Property Trust Inc.	CXP
Easterly Government Properties	DEA
Equity Commonwealth	EQC
Empire State Realty Trust	ESRT
Franklin Street Properties Corp.	FSP
Highwoods Properties, Inc.	HIW
Hudson Pacific Properties, Inc.	HPP
Kilroy Realty Corporation	KRC
Corporate Office Properties Trust	OFC
Office Properties Income Trust	OPI
Piedmont Office Realty Trust, Inc.	PDM
Paramount Group, Inc.	PGRE
SL Green Realty Corp	SLG
Vornado Realty Trust	VNO
Douglas Emmett, Inc.	DEI
City Office REIT, Inc.	CIO
New York City REIT, Inc.	NYC

We use a two-stage Fama-MacBeth procedure. In the first stage using the time-series, we estimate 36-month rolling-window regressions of each REIT's return on the three factor returns; i.e., we estimate equation (8) for each REIT separately. In the second cross-sectional step, we regress the realized return each month on the betas for that month. The market price of risk estimates are the average of the monthly slope estimates of the second step. We use only the months prior to the onset of the pandemic (December 2014–December 2019)

when computing this average. Since the WFH index saw unusually high realizations during the pandemic, inclusion of the pandemic months would lead one to confuse realized with expected returns, while in fact the two are negatively correlated. We obtain $\hat{\lambda}^{wfh} = -7.0\%$ annualized (t -stat is -0.52 but the sample is short to reliably estimate this coefficient).¹⁸

The negative market price of risk for WFH risk means that states of the world where the WFH risk factor was large and positive are bad states of the world. This is intuitive, as those are periods where the coronavirus pandemic surges. Conversely, negative returns to WFH, such as Nov 8, 2020 when the vaccine discovery news first broke, are good states of the world.

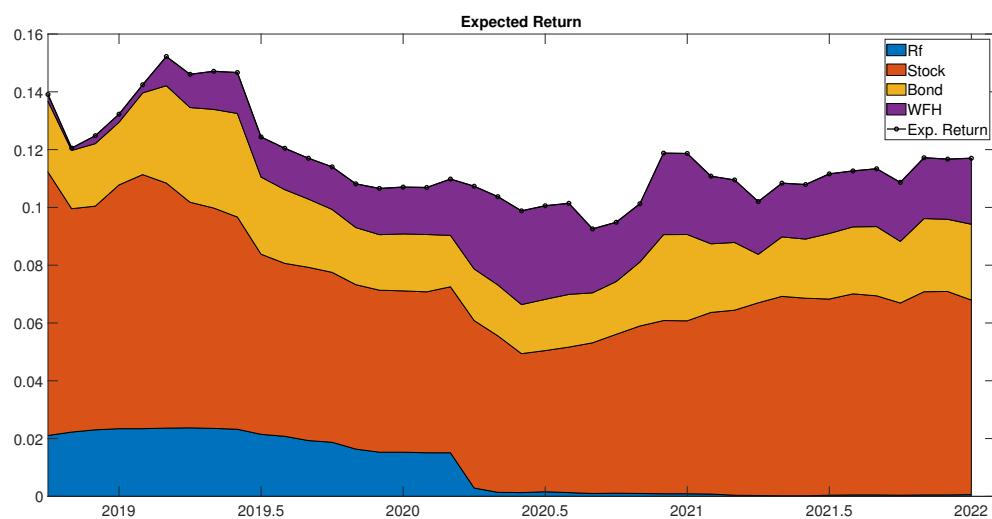
A.5 Expected Returns

For the risk prices on stocks and bond, we use the sample average of the estimated risk premia in the post-1994 period: $\lambda^m = 7.81\%$ and $\lambda^b = 2.91\%$. For the WFH risk price we use $\lambda^{wfh} = -7.0\%$, as estimated above. We combine the three time-varying betas from Figure 20 with the market price of risk estimates to form the expected return on office REITS as per equation (7). Figure 21 plots the resulting expected return. While the contribution from stocks and bond market risk shrinks over the course of the pandemic, by virtue of the declining stock and bond betas, the contribution from the WFH risk exposure (in purple) is substantial. WFH risk contributes about 2–3% points to the expected return on office during the pandemic.

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

¹⁸Repeating the exercise with weekly instead of monthly return data and the 52-week rolling window betas, we obtain $\hat{\lambda}^{wfh} = -10.2\%$ (t -stat is -0.84).

Figure 21: Expected Return of Office REITs During Covid



B Model Derivation

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

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

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

B.1 Revenue.

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

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

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 ,

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

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

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

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

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

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

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

$$\begin{aligned} R_{t+1}^O &= \chi \sum_{j=0}^{\infty} (1 - \chi)^j R_{t+1-k}^m \\ R_{t+1}^O &= \chi R_{t+1}^m + \chi(1 - \chi)R_t^m + \chi(1 - \chi)^2 R_{t-1}^m + \chi(1 - \chi)^3 R_{t-2}^m + \dots \\ R_{t+1}^O &= \chi R_{t+1}^m + (1 - \chi) \left[\chi R_t^m + \chi(1 - \chi)R_{t-1}^m + \chi(1 - \chi)^2 R_{t-2}^m + \dots \right] \\ R_{t+1}^O &= (1 - \chi)R_t^O + \chi R_{t+1}^m. \end{aligned}$$

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

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

We define the state variable \hat{R}_t^O as,

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

Next, we want to find the law of motion for the scaled state variable \hat{R}_{t+1}^O :

$$\begin{aligned}
\hat{R}_{t+1}^O &= \frac{R_{t+1}^O}{R_{t+1}^m} \\
\hat{R}_{t+1}^O &= \frac{(1-\chi)R_t^O + \chi R_{t+1}^m}{R_{t+1}^m} \\
\hat{R}_{t+1}^O &= \frac{(1-\chi)R_t^O}{R_{t+1}^m} + \chi \\
\hat{R}_{t+1}^O &= \frac{(1-\chi)\hat{R}_t^O R_t^m}{R_{t+1}^m} + \chi \\
\hat{R}_{t+1}^O &= \frac{(1-\chi)\hat{R}_t^O}{1 + \epsilon_{t+1}(z')} + \chi.
\end{aligned}$$

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

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

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

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

The expected PDV of revenues is written as

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

The scaled version of revenues can be written as:

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

which solves the following Bellman equation:

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

Finally, we get V_t^R by

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

B.2 Costs

The building costs are written as:

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

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

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

We define scaled costs as:

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

Therefore, we have:

$$\begin{aligned} \widehat{Cost}_{t+1}(\hat{Q}_t^O, z') &= c_{t+1}^{fix}(z') + \hat{Q}_t^O c_{t+1}^{var}(z') + \\ &\quad \left[\hat{Q}_t^O \chi s_{t+1}^O(z') LC_{t+1}^R(z') + (1 - \hat{Q}_t^O) s_{t+1}^V(z') LC_{t+1}^N(z') \right] (1 + \epsilon(z')), \end{aligned}$$

where

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

The expected PDV of costs is written as:

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

The scaled version is:

$$\hat{V}_t^C = \frac{V_t^C}{\bar{Q}_t R_t^m}.$$

which solves the Bellman equation

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

Finally, we get V_t^C by

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

B.3 Closed-form solutions

First, we define matrix notations for parameters:

$$\mathbb{1}_{4 \times 1} = \begin{bmatrix} 1, 1, 1, 1 \end{bmatrix}'$$

$$E_{4 \times 4} = \begin{bmatrix} \epsilon_{4 \times 1}, \epsilon_{4 \times 1}, \epsilon_{4 \times 1}, \epsilon_{4 \times 1} \end{bmatrix}'$$

$$H_{4 \times 4} = \begin{bmatrix} \eta_{4 \times 1}, \eta_{4 \times 1}, \eta_{4 \times 1}, \eta_{4 \times 1} \end{bmatrix}'$$

$$S_{4 \times 4}^O = \begin{bmatrix} s_{4 \times 1}^O, s_{4 \times 1}^O, s_{4 \times 1}^O, s_{4 \times 1}^O \end{bmatrix}'$$

$$S_{4x4}^V = \left[s_{4x1}^V, s_{4x1}^V, s_{4x1}^V, s_{4x1}^V \right]'$$

B.3.1 Cost Valuation

We first short hand the expression of $\widehat{Cost}_{t+1}(\hat{Q}_t^O, z')$, which is a linear function w.r.t. \hat{Q}_t^O , as:

$$\widehat{Cost}_{t+1}(\hat{Q}_t^O, z') = a(z') + b(z') \cdot \hat{Q}_t^O$$

where

$$a(z') = c_{t+1}^{fix}(z') + (1 + \epsilon(z')) \cdot s_{t+1}^V(z') LC_{t+1}^N(z'),$$

$$b(z') = c_{t+1}^{var}(z') + (1 + \epsilon(z')) \cdot \left[\chi s_{t+1}^O(z') LC_{t+1}^R(z') - s_{t+1}^V(z') LC_{t+1}^N(z') \right]$$

Then, we take the derivative (w.r.t. \hat{Q}_t^O) of cost valuation Bellman equation:

$$\begin{aligned} \frac{\partial \hat{V}_t^C}{\partial \hat{Q}_t^O}(\hat{Q}_t^O, z) &= \sum_{z'} \pi(z'|z) M(z'|z) \left\{ b(z') + (1 + \eta(z'))(1 + \epsilon(z')) \frac{\partial \hat{V}_{t+1}^C}{\partial \hat{Q}_t^O}(\hat{Q}_{t+1}^O, z') \right\} \\ &= \sum_{z'} \pi(z'|z) M(z'|z) \left\{ b(z') + (1 + \epsilon(z'))(1 - \chi + \chi s_{t+1}^O(z') - s_{t+1}^V(z')) \frac{\partial \hat{V}_{t+1}^C}{\partial \hat{Q}_{t+1}^O}(\hat{Q}_{t+1}^O, z') \right\}. \end{aligned}$$

Notice that the instantaneous reward term, $b(z')$, is independent to \hat{Q}_t^O . Thus, $\frac{\partial \hat{V}_t^C}{\partial \hat{Q}_t^O}(\hat{Q}_t^O, z)$ is only a function of z by checking the valuation in a infinite sum form:

$$\frac{\partial \hat{V}_t^C}{\partial \hat{Q}_t^O}(\hat{Q}_t^O, z) = \sum_{\tau=1}^{\infty} \mathbb{E}_t [M(z_{t+\tau}|z) \cdot b(z_{t+\tau})].$$

Thus, by taking integral of \hat{Q}_t^O , we can conclude that \hat{V}^C is a linear function w.r.t. \hat{Q}_t^O :

$$\hat{V}_{4x1}^C = a_{4x1}^C(z) + b_{4x1}^C(z) \cdot \hat{Q}_t^O$$

where¹⁹

$$b_{4x1}^C(z_{4x1}) = \left(I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ \left(1 - \chi + \chi S_{4x4}^O - S_{4x4}^V \right) \right)_{4x4}^{-1} \cdot \\ (\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \left(c_{4x1}^{var} + (1 + \epsilon_{4x1}) \circ \left(\chi S_{4x1}^O \circ LC_{4x1}^R - s_{4x1}^V \circ LC_{4x1}^N \right) \right)_{4x1}.$$

Then, we look back the original valuation function of cost, and equation becomes a linear equation for the only unknown, a^C , and we solve it using the inverse method:

$$a_{4x1}^C(z_{4x1}) = (I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ (1 + H_{4x4}))_{4x4}^{-1} \cdot \\ (\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \left(c_{4x1}^{fix} + (1 + \epsilon_{4x1}) \circ \left(s_{4x1}^V \circ LC_{4x1}^N + b_{4x1}^C \circ s_{4x1}^V \right) \right)_{4x1}.$$

B.3.2 Revenue Valuation

The revenue valuation problem is very similar to the cost valuation problem, but now the valuation function depends on both \hat{Q}_t^O and \hat{R}_t^O . So we first look at the Bellman equation for $\frac{\partial^2 \hat{V}_t^R}{\partial \hat{Q}_t^O \partial \hat{R}_t^O}$ and find it is independent to \hat{Q}_t^O or \hat{R}_t^O :

$$\frac{\partial^2 \hat{V}_t^R}{\partial \hat{Q}_t^O \partial \hat{R}_t^O} = d^R(z) \tag{9}$$

where

$$d_{4x1}^R(z_{4x1}) = \left(I - \pi_{4x4} \circ M_{4x4} \circ (1 - \chi) \circ \left(1 - \chi + \chi S_{4x4}^O - S_{4x4}^V \right) \right)_{4x4}^{-1} \cdot \\ (\pi_{4x4} \circ M_{4x4})_{4x4} \cdot (1 - \chi \cdot \mathbb{1}_{4x1})_{4x1}.$$

Next, we integrate equation (9) by \hat{Q}_t^O :

$$\frac{\partial \hat{V}_t^R}{\partial \hat{R}_t^O} = c^R(\hat{R}_t^O, z) + d^R(z) \cdot \hat{Q}_t^O.$$

¹⁹We use \circ to represent element-wise multiplication for metrics, and \cdot for matrix dot product.

Notice that the instantaneous reward term for the Bellman equation for $\frac{\partial \hat{V}_t^R}{\partial \hat{R}_t^O}$ is independent to \hat{R}_t^O :

$$\frac{\partial \widehat{Rev}_{t+1}}{\partial \hat{R}_t^O} = (1 - \chi) \cdot \hat{Q}_t^O. \quad (10)$$

Thus, we can conclude:

$$c^R(\hat{R}_t^O, z) = c^R(z),$$

and we can solve $c^R(z)$ in this linear system:

$$\begin{aligned} c_{4x1}^R(z_{4x1}) &= (I - \pi_{4x4} \circ M_{4x4} \circ (1 + H_{4x4}) \circ (1 - \chi))_{4x4}^{-1} \cdot \\ &\quad (\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \left((1 - \chi) \circ s_{4x1}^V \circ d_{4x1}^R \right)_{4x1}. \end{aligned}$$

Following the same logic, by taking integral w.r.t. \hat{R}_t^O in equation (9) and check the independence of instantaneous reward:

$$\frac{\partial \hat{V}_t^R}{\partial \hat{Q}_t^O} = b^R(z) + d^R(z) \cdot \hat{R}_t^O \quad (11)$$

where

$$\begin{aligned} b_{4x1}^R(z_{4x1}) &= \left(I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ \left(1 - \chi + \chi S_{4x4}^O - S_{4x4}^V \right) \right)_{4x4}^{-1} \cdot \\ &\quad (\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \left((1 + \epsilon_{4x1}) \circ \left((\chi s_{4x1}^O - s_{4x1}^V) \circ (1 + \chi d_{4x1}^R) + (1 - \chi) \chi d_{4x1}^R \right) \right)_{4x1}. \end{aligned}$$

Then, we integrate equation (10) w.r.t. \hat{R}_t^O and equation (11) w.r.t. \hat{Q}_t^O , we get:

$$\begin{aligned} \hat{V}_t^R &= a_R(\hat{R}_t^O, z) + c(z) \cdot \hat{R}_t^O + d(z) \cdot \hat{Q}_t^O \cdot \hat{R}_t^O \\ &= a_Q(\hat{Q}_t^O, z) + b(z) \cdot \hat{Q}_t^O + d(z) \cdot \hat{Q}_t^O \cdot \hat{R}_t^O. \end{aligned}$$

By comparing terms, we can conclude that

$$\hat{V}_t^R = a^R(z) + b^R(z) \cdot \hat{Q}_t^O + c^R(z) \cdot \hat{R}_t^O + d^R(z) \cdot \hat{Q}_t^O \cdot \hat{R}_t^O$$

and solve the intercept term in the linear system:

$$a_{4x1}^R(z_{4x1}) = (I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ (1 + H_{4x4}))_{4x4}^{-1} \cdot \\ (\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \left((1 + \epsilon_{4x1}) \circ \left(s_{4x1}^V \circ (1 + b_{4x1}^R + \chi d_{4x1}^R) + \chi (1 + \eta_{4x1}) \circ c_{4x1}^R \right) \right)_{4x1}.$$

B.4 Strip Decomposition

The price of a property is the expected PDV of its future cash-flows. By value additivity, this is also the sum of prices of each cash-flow strip:

$$V_t = V_t^{(1)} + V_t^{(2)} + \dots = \sum_{j=1}^{\infty} V_t^{(j)} = \sum_{j=1}^{\infty} V_t^{R,(j)} - \sum_{j=1}^{\infty} V_t^{C,(j)}.$$

The last equality expresses the price of each NOI strip as the difference between the corresponding revenue strip and cost strip, again using value additivity.

The revenue strips can be priced recursively:

$$V_t^{R,(j)} = \mathbb{E}_t \left[M_{t,t+j} V_{t+1}^{R,(j-1)} \right]$$

starting from

$$V_t^{R,(1)} = \mathbb{E}_t [M_{t,t+1} Rev_{t+1}].$$

Scaling by potential gross revenue

$$\widehat{V}_t^{R,(j)} = \frac{V_t^{R,(j)}}{\widehat{Q}_t R_t^m} = \mathbb{E}_t \left[M_{t,t+j} \widehat{V}_{t+1}^{R,(j-1)} (1 + \epsilon_{t+1}) (1 + \eta_{t+1}) \right]$$

starting from

$$\widehat{V}_t^{R,(1)} = \mathbb{E}_t \left[M_{t,t+1} \widehat{Rev}_{t+1} \right]$$

since

$$\frac{\widehat{Q}_{t+1} R_{t+1}^m}{\widehat{Q}_t R_t^m} = (1 + \epsilon_{t+1}) (1 + \eta_{t+1}).$$

There is a closed-form expression for each $\hat{V}_t^{R,(j)}$ that can be established using the same procedure we used above to obtain the closed-form solution for the entire claim's scaled valuation ratio \hat{V}_t^R .

$$\hat{V}_t^{R,(j)} = a^{R,(j)}(z) + b^{R,(j)}(z) \cdot \hat{Q}_t^O + c^{R,(j)}(z) \cdot \hat{R}_t^O + d^{R,(j)}(z) \cdot \hat{Q}_t^O \cdot \hat{R}_t^O,$$

for suitably-defined coefficients $a^{R,(j)}(z)$, $b^{R,(j)}(z)$, $c^{R,(j)}(z)$, and $d^{R,(j)}(z)$.

The logic is similar for the scaled price of the cost strips.

$$\hat{V}_t^{C,(j)} = a^{C,(j)}(z) + b^{C,(j)}(z) \cdot \hat{Q}_t^O,$$

for suitably-defined coefficients $a^{C,(j)}(z)$ and $b^{C,(j)}(z)$.

C Calibration Algorithm

The following describes the steps in the calibration algorithm for the universe of NYC office buildings (All NYC) and the subset of A+ buildings (NYC A+). We set the depreciation to 2.7% in both calibrations, a realistic annual depreciation rate for commercial office. The calibration for All NYC takes the persistence parameter of the WFH state, p , as given. This parameter is pinned down from the A+ calibration. Conversely, the calibration for NYC A+ takes the parameter $\Delta\eta$ as given. This parameter is pinned down from the All NYC calibration. Hence, the two calibrations are interdependent: they solve a fixed-point problem.

C.1 All NYC, given p

1. Keep only office buildings and exclude subleases in the CompStak data set of leases for NYC.
2. Calculate the average lease term for all leases in NYC. Set χ equal to the reciprocal.
3. Estimate ε from data:

- (a) To estimate $\varepsilon(E)$ and $\varepsilon(R)$, first calculate sf-weighted NER for each month, and take the 6-month moving average. Use data from January 2000 (start of CompStak) until December 2019.
- (b) If more than 6 months of the 1-year window falls in recession, then the year is considered to be a recession; otherwise it is considered to be an expansion. Use the leasing cycle definition instead of the business cycle.
- (c) Compute the annual growth rate of the six-month moving average, and take the average separately for expansions and recessions.
- (d) Estimate $\epsilon(WFHR)$ as the realized NER growth between December 2019 and December 2020, and $\epsilon(WFHE)$ as the annualized realized rent growth between December 2020 and May 2022.
- (e) Since the values for $\varepsilon(E)$ and $\varepsilon(R)$ are determined based on the leasing cycle rather than the business cycle, adjust all four $\varepsilon(z)$ parameters by a constant so that the unconditional average NER growth in the model, which uses the Markov chain $\pi(z'|z)$ estimated on the business cycle, equals the sample average NER growth.

4. Estimate $\eta(E)$ and $\eta(R)$ from data:

- (a) Compute the growth rate in floor space in year t as the newly constructed office square feet in year t relative to the total square feet of office space built before year t for each year from 1970–2019. This uses the full history of construction years in our CompStak dataset.
- (b) Year t is a recession when more than six months of that year is in recession.
- (c) We take the average the construction growth rate across expansions and recessions.
- (d) Finally, we subtract the rate of depreciation to arrive at $\eta(E)$ and $\eta(R)$

5. Set $\eta(WFHE) = \eta(E) + \Delta\eta$ and $\eta(WFHR) = \eta(R) + \Delta\eta$. Find the $\Delta\eta$ such that the

long-run growth rate of potential rent in the All NYC is zero:

$$\sum_z \pi(z)(1 + \varepsilon(z))(1 + \eta(z)) = 1,$$

where $\pi(z)$ is the 4×1 ergodic distribution of the 4×4 Markov Chain $\pi(z'|z)$.

6. Estimate the four parameters $\{s^O(E), s^O(R), s^V(E), s^V(R)\}$ to match the following four moments in quarterly Manhattan office occupancy rate data for from 1987.Q1 to 2020.Q1:
 - (a) empirical mean
 - (b) empirical standard deviation
 - (c) empirical min - 0.5%
 - (d) empirical max + 0.5%
7. Assume that the four parameters $\{s^O(WFHE), s^O(WFHR), s^V(WFHE), s^V(WFHR)\}$ are shifted by a common factor 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 nine quarters from 2020.Q2–2022.Q2. These dynamics are given by the model:

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

Simulate the law of motion for occupancy from 1930 until 2019, under the observed sequence of expansions and recessions, to arrive at the initial condition for \hat{Q}^O in 2020.Q1. Next, we simulate the occupancy process forward for the next nine quarters assuming that the first four quarters are WFH-R observations and the last five are WFH-E. We find the δ that minimizes the distance between the model and the data.

C.2 NYC A+, given $\Delta\eta$

The calibration for the A+ office cash flows is based on the subset of leases in A+ buildings. It follows the same steps as outlined above for All NYC, with the following modifications:

- 3.(d) The observed value for $\epsilon(WFHE)$ in step 3(d) is implausible.²⁰ We set $\epsilon(WFHE, A+) = \epsilon(WFHE, All) - \epsilon(E, All) + \epsilon(E, A+)$. This preserves the features that A+ market rent growth is less cyclical than All NYC rent growth and that A+ market rent growth in WFH-E is lower than in E.
5. The NYC A+ calibration takes $\Delta\eta$ from the All NYC calibration.
6. We use data from NAREIT on office sector occupancy from 2000.Q1 to 2020.Q1 to calibrate $\{s^O(E), s^O(R), s^V(E), s^V(R)\}$. We target a minimum occupancy rate equal to the empirical minimum—6.5%—because the A+ occupancy data is missing the 1990s, the worst historical period for office occupancy.
8. Given all other parameters, find p to match the observed realized return on NYC-centric office REITS between December 31, 2019 and December 31, 2020, after adjusting for leverage. See the discussion in Section 3.4.

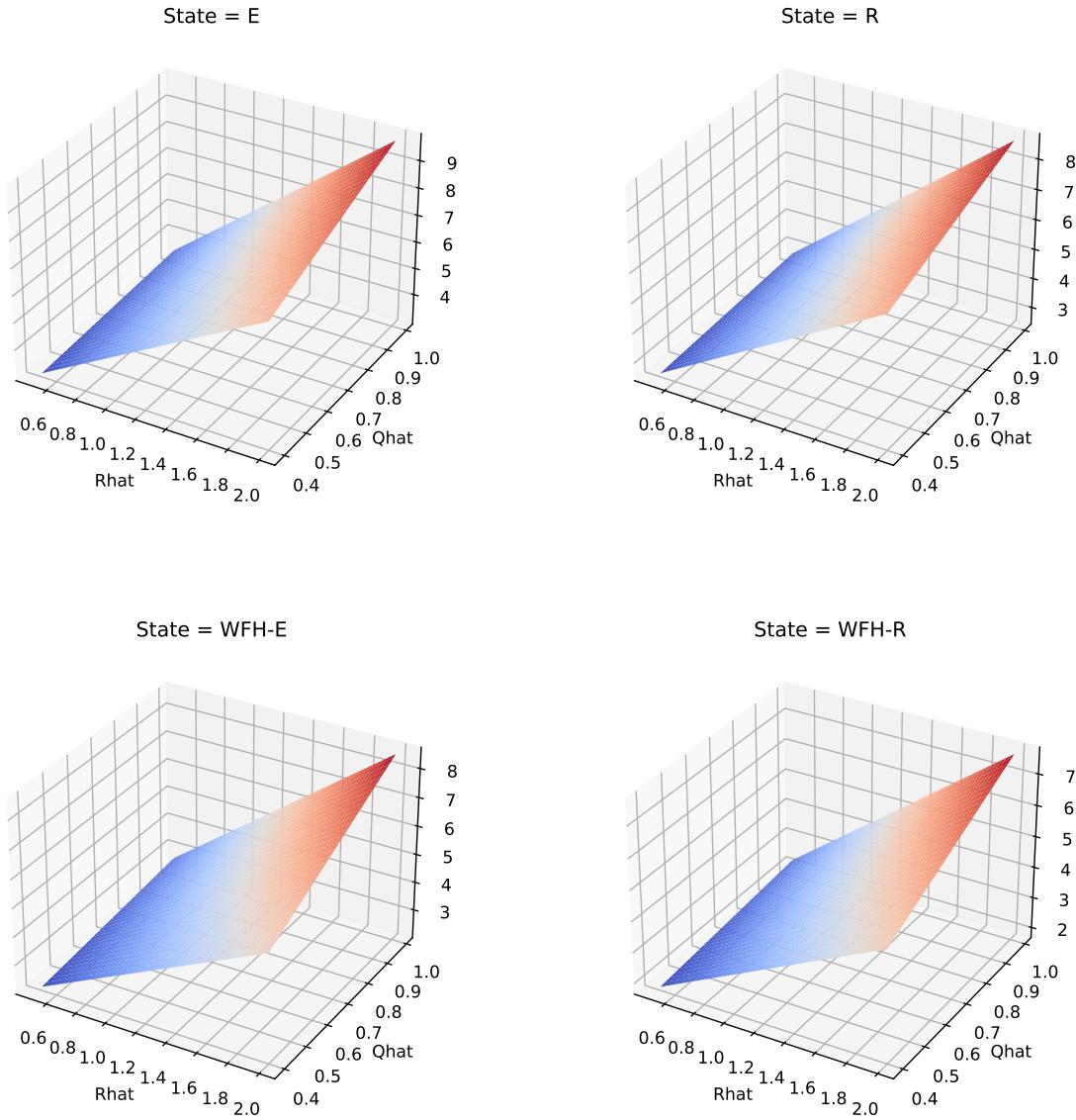
Figure 22 shows the valuation ratio for office \hat{V} conditional on expansion, recession, WFH-expansion and WFH-recession for the All NYC calibration. The x-axis plots the grid for \hat{Q}^O and the y-axis shows the grid for \hat{R}^O . Office valuation ratios are increasing in both occupancy \hat{Q}^O and rent premium \hat{R}^O .

D Results for NYC A+ Market

Appendix Table 9 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

²⁰This is not surprising. The data are based on one realization from a transition from WFH-R to WFH-E, which may not be a good measure of the average rent growth conditional on being in WFH-E.

Figure 22: \hat{V} for All NYC Market by States

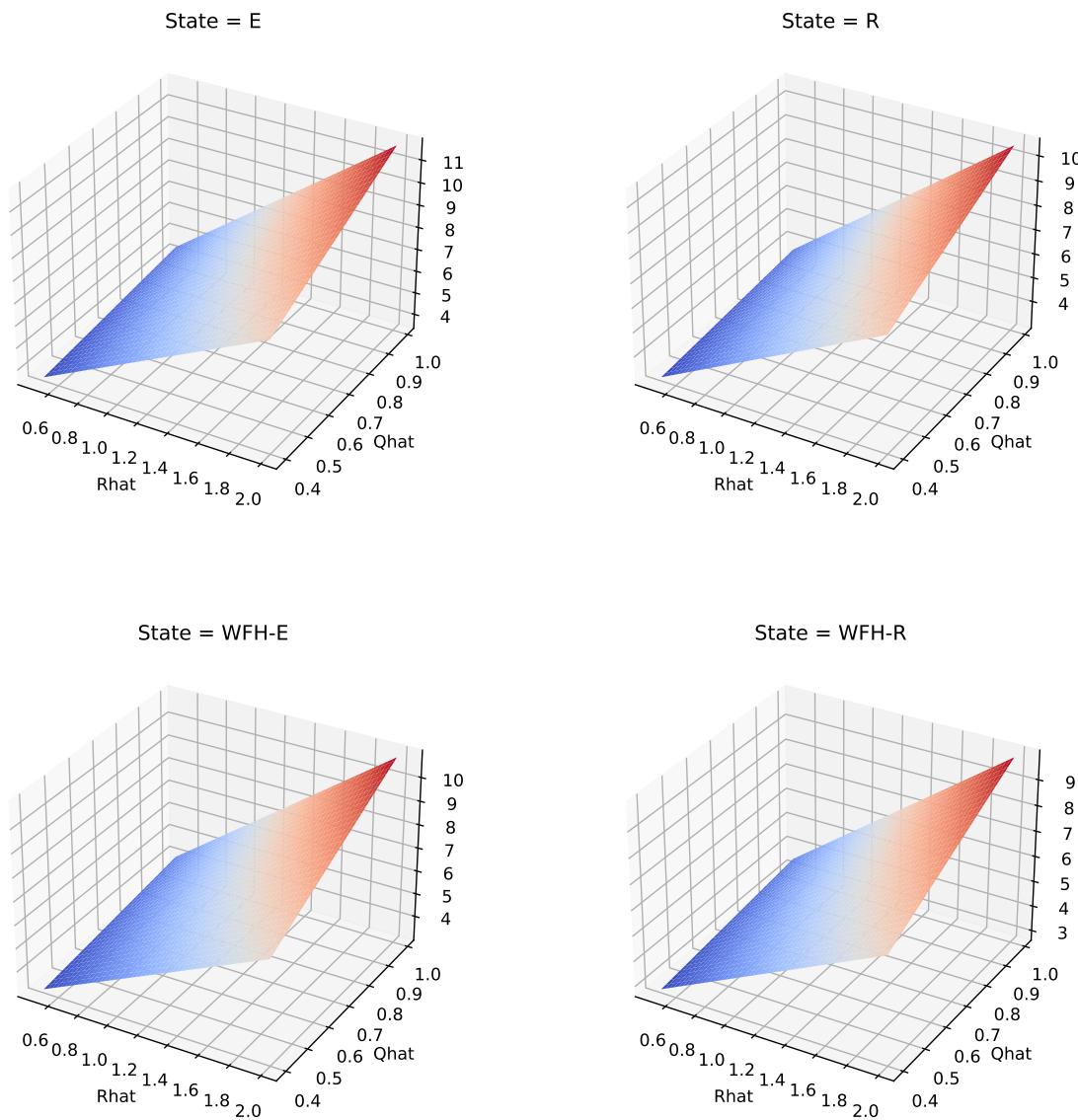


lower vacancy levels than the market as a whole, on average as well as in the WFH states. Appendix Figure 23 shows the valuation ratio \hat{V} in each state as a function of occupancy and rent state variables.

Table 9: Model Solution for NYC All Calibration

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.0656	0.0623	0.0828	0.0625	0.0748
Office $\mathbb{E}[Ret] - 1$	0.0645	0.0516	0.1346	0.0459	0.1184
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0496	0.0432	0.0879	0.0375	0.0716
$\mathbb{E}[g_t]$	-0.0024	-0.0179	0.0989	-0.0289	0.0213
Vacancy rate = $1 - \widehat{Q}^O$	0.0983	0.0819	0.1220	0.1278	0.1553
$\widehat{\text{Rev}}$	0.8228	0.8158	0.9340	0.7658	0.8069
$\widehat{\text{Cost}}$	0.4228	0.4279	0.4183	0.4114	0.4050
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.3994	0.3874	0.5151	0.3539	0.4013
\widehat{V}^R	10.7146	11.0337	10.0413	10.3574	9.3590
\widehat{V}^C	4.7105	4.9033	3.9135	4.7601	4.0601
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	6.0041	6.1304	6.1278	5.5973	5.2988

Figure 23: \hat{V} for NYC A+ Market by States



E Calibration to Other Markets

We repeat the calibration procedure discussed in the main text and in Appendix C for San Francisco and Austin. 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, construction rates during the pandemic (WFHR and WFHE) are set equal to their pre-pandemic counterparts (R and E) minus an adjustment factor. The adjustment factor for SF (Austin) corrects the NYC adjustment factor for differences between SF (Austin) and NYC in the pandemic-minus-pre-pandemic construction rate change obtained from the Cushman & Wakefield inventory data. Due to the incompleteness of building coverage in Compstak, estimation of η for San Francisco and Austin starts from 1980. We use contractual occupancy rate data from Cushman and Wakefield to calibrate s^O and s^V before and during the pandemic. We leave the office depreciation rate and the operational cost parameters the same as in the NYC calibration. Naturally, we assume that the dynamics of the aggregate state variable $\pi(z', z)$ are common across markets, as well as the market prices of risk $M(z', z)$.

Table 10 shows the calibrated parameters for San Francisco and 11 shows those for Austin. Table 12 and 13 show the main moments for San Francisco and Austin, respectively. The SF office market is riskier than the NYC market, featuring a rent cycle of greater amplitude which translates into a higher risk premium and cap rate. The opposite is true for Austin. Figure 24 plots fan charts for occupancy rates, revenues, NOI and cap rates for San Francisco and Austin.

Table 10: Calibration for San Francisco

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.1346	-0.2130	-0.0050	-0.2001
Supply growth	η	-0.0192	-0.0101	-0.0487	-0.0396
Lease renewal share	s^O	0.8500	0.6766	0.3541	0.2819
New leasing share	s^V	0.2369	0.1948	0.0987	0.0812

Table 11: Calibration for Austin

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0372	-0.0546	0.0674	-0.0634
Supply growth	η	0.0002	0.0076	-0.0071	0.0003
Lease renewal share	s^O	0.9215	0.9215	0.6115	0.6115
New leasing share	s^V	0.2030	0.1000	0.1347	0.0663

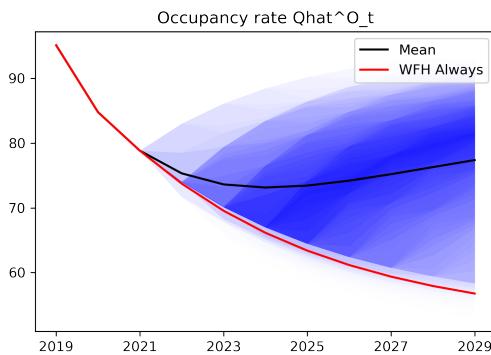
Table 12: Model Solution for San Francisco Calibration

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.0913	0.0801	0.1320	0.0922	0.1333
Office $\mathbb{E}[Ret] - 1$	0.1258	0.1028	0.2383	0.1058	0.2063
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.1109	0.0944	0.1916	0.0974	0.1596
$\mathbb{E}[g_t]$	0.0285	-0.0007	0.2245	-0.0281	0.0838
Vacancy rate = $1 - \widehat{Q}^O$	0.1546	0.0992	0.1568	0.3148	0.3462
$\widehat{\text{Rev}}$	0.7735	0.7692	0.9612	0.6475	0.7572
$\widehat{\text{Cost}}$	0.4230	0.4390	0.4237	0.3760	0.3671
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.3505	0.3302	0.5375	0.2715	0.3901
\widehat{V}^R	7.2999	8.0135	6.6782	5.6732	4.9550
\widehat{V}^C	3.4976	3.9494	2.6910	2.7723	2.0816
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	3.8023	4.0641	3.9872	2.9009	2.8734

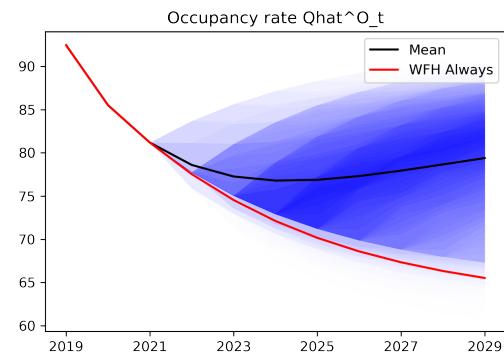
Table 13: Model Solution for Austin Calibration

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.0446	0.0449	0.0562	0.0341	0.0465
Office $\mathbb{E}[Ret] - 1$	0.0743	0.0534	0.1500	0.0685	0.1844
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0594	0.0450	0.1033	0.0602	0.1376
$\mathbb{E}[g_t]$	0.0273	0.0248	0.0658	-0.0050	0.0827
Vacancy rate = $1 - \widehat{Q}^O$	0.1493	0.1126	0.1384	0.2619	0.2907
$\widehat{\text{Rev}}$	0.8000	0.8325	0.8669	0.6531	0.6903
$\widehat{\text{Cost}}$	0.4254	0.4360	0.4287	0.3930	0.3845
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.3746	0.3965	0.4382	0.2601	0.3057
\widehat{V}^R	17.1823	17.9455	15.4817	16.4288	13.7847
\widehat{V}^C	8.8143	9.1314	7.7056	8.8433	7.2517
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	8.3680	8.8141	7.7761	7.5855	6.5330

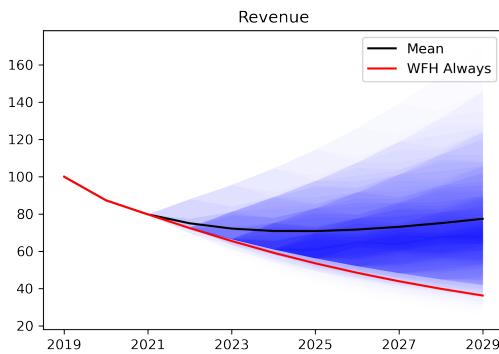
Figure 24: Fan Charts for San Francisco and Austin



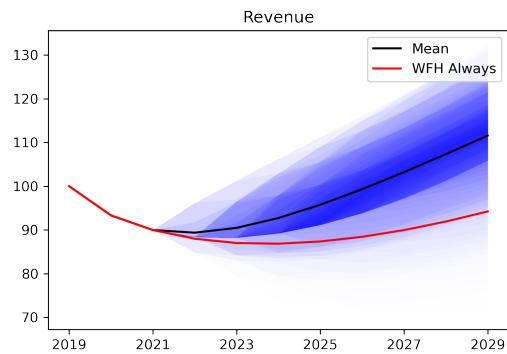
(a) San Francisco: Occupancy



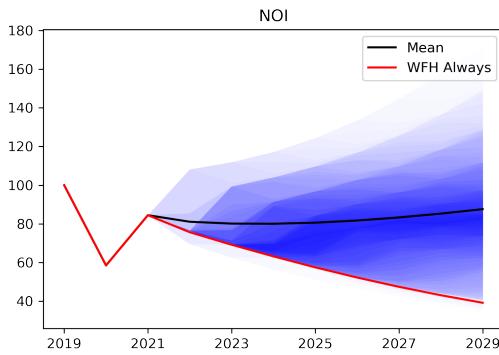
(b) Austin: Occupancy



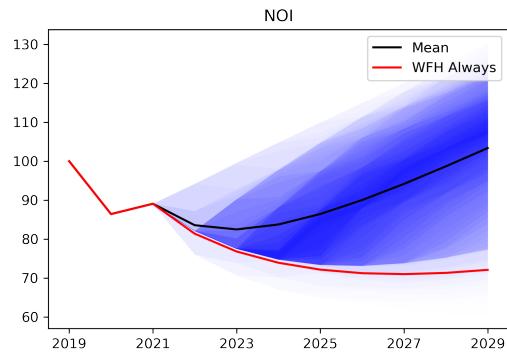
(c) San Francisco: Revenue



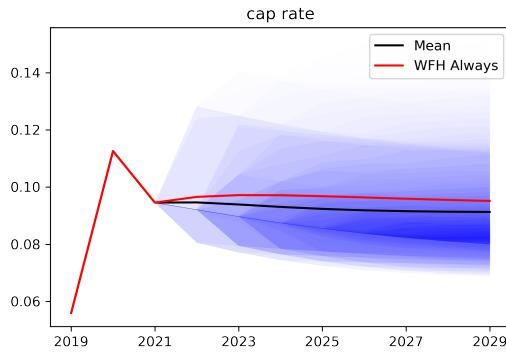
(d) Austin: Revenue



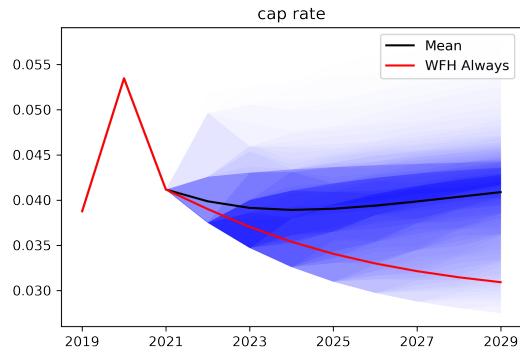
(e) San Francisco: NOI



(f) Austin: NOI



(g) San Francisco: Cap Rate



(h) Austin: Cap Rate