Work From Home and the Office Real Estate Apocalypse

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Abstract

We study the impact of remote work on the commercial office sector. We document large shifts in lease revenues, office occupancy, lease renewal rates, lease durations, and market rents as firms shifted to remote work in the wake of the Covid-19 pandemic. We show that the pandemic has had large effects on both current and expected future cash flows for office buildings. Remote work also changes the risk premium on office real estate. We revalue the stock of New York City commercial office buildings taking into account pandemic-induced cash flow and discount rate effects. We find a 32% decline in office values in 2020 and 28% in the longer-run, the latter representing a $500 billion value destruction. Higher quality office buildings were somewhat buffered against these trends due to a flight to quality, while lower quality office buildings see much more dramatic swings. These valuation changes have repercussions for local public finances and financial sector 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"Commuting to office work is obsolete.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 50% by May 2022. In the intervening period, companies have learned how to effectively work from home. Many corporate leaders have announced permanent remote or hybrid work arrangements, and several have begun to shrink their physical footprint. These shifts in projected office demand have led to concerns that commercial office buildings may become a stranded asset in the wake of the technological disruptions resulting from remote work. Because office assets are often financed with debt which resides on banks' balance sheets and in CMBS portfolios, such declines in value would have large 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 offices and the adjacent retail space to provide public goods and services.

In this paper, we ask what these changes in current and expected future remote work arrangements imply for the value of office buildings. To answer this challenging question, we combine new data with a new asset pricing model.

To fix ideas, consider the three key forces behind the shifts in office values through the lens of a simple Campbell and Shiller (1988) decomposition. We can express the current

[1] Investable commercial real estate assets were worth about $4.7 trillion at the end of 2019, of which office represents a considerable 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).

value of offices p_t as the current cash flow d_t, the expected present discounted value (PDV) of future cash flows, and the expected PDV of future returns:

$$p_t = \frac{k}{1-\rho} + d_t + \sum_{j=0}^{\infty} \mathbb{E}_t[\rho^j \Delta d_{t+1+j}] - \sum_{j=0}^{\infty} \mathbb{E}_t[\rho^j r_{t+1+j}]$$

Taking expectations at t of the price at time $t+1$, we can express the shock to office valuations in the pandemic relative to what was expected prior to the pandemic in terms of news about current and future cash flows and news about future returns:

$$p_{t+1} - \mathbb{E}_t[p_{t+1}] = \underbrace{(d_{t+1} - \mathbb{E}_t[d_{t+1}])}_{\text{Shock to current CF}} + \underbrace{(\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+1+j}}_{\text{Shock to exp. future CF}} - \underbrace{(\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^{j-1} r_{t+1+j}}_{\text{Shock to exp. future returns}} . \quad (1)$$

First, we analyze the shock to current cash flows, the first term in equation (1). Using a unique data set from CompStak, we study lease-level data for 105 office markets throughout the United States over the period from 2000 until December 2021. We document an 8 percentage point decrease in lease revenue between January 2020 and December 2021. This decline entirely reflects decreases in the quantity of in-force leases rather than shifts in rents on in-force leases. The quantity of newly-signed leases in our data set falls from 300 million square feet per year just before the pandemic to below 100 million square feet in the last quarter of 2021. Rents on in-force lease contracts growth throughout the pandemic. Rents on newly-signed leases fell by 9.9% in real terms between January 2020 and December 2021, before reversing sharply to pre-pandemic levels by the end of 2021.

We measure firms' remote work plans by analyzing remote-work terms mentioned in job postings from Ladders, to establish a negative correlation between tenants' remote-worker hiring plans and their reductions in leased office space.

The effects on lease revenue is not seen uniformly across properties. We find some 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 in the pandemic. Their rents on newly-signed leases do not fall or even go up, in contrast with the rest of the office stock. This is consistent with the anecdotal evidence that firms need to improve office quality to induce workers to return to the office given new remote options. By contrast, lower quality office stock appears to be a more substantially stranded asset, given lower demand, raising questions about whether these assets can be ultimately repurposed towards other uses. Because a large fraction of leases (66% in the U.S., 73% in New York) have not come up for renewal yet since the start of the pandemic, and because vacancy rates are already at 30-year highs in several major markets (20.4% in New York in 2021.Q4), rents may not have bottomed out yet.

Second, because valuations are forward looking and reflect expectations of future cash flows and future returns, the second and third terms in equation (1), we need an asset pricing model. We build a new model adapted to the valuation of commercial real estate assets that features long lease durations, market rent risk, and supply growth risk. We model property revenues and costs, to arrive at net operating income. A property is a portfolio of long-term leases. The model aggregates to let us compute the value of (a segment of) the office market as a portfolio of office properties. There is aggregate risk in the form of business cycles. There also is 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 states.

We calibrate the model to New York City's office market. It matches market rent, supply, and vacancy dynamics in the data. This includes the sharp increase in office vacancy rates to 20% in the 2019–2020 transition. 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 we create. The WFH risk factor goes long in publicly-listed companies which support remote work practices (i.e., Zoom) and goes short publicly-listed companies which are reliant on physical presence (i.e., cruise lines).

A key parameter that affects the change in office valuations due to remote work is the persistence of remote/hybrid work practices. We back out this parameter from the (unlevered) observed stock return on NYC-centric office REITs between January 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 which relies on Compstak data. The model matches the observed office return for an annual persistence parameter of 0.87, indicating that office REIT investors believe remote-work practices to be long-lasting.

With this parameter in hand, we return to the full NYC office market calibration. We obtain a 32.95% reduction in the value of the entire NYC office stock between the end of 2019 and the end of 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 rises from the depths of its 2021 values and the economy returns to the no-WFH state with some probability. These mean-reversion forces push office valuations towards an average value in 2029 is about 28% below 2019 values. Along paths where the economy remains in the WFH state for ten years, office values in 2029 remain about 38% below their 2019 values. Hence, there is substantial uncertainty about future office values, WFH risk, that our approach quantifies.

What do these numbers imply for the value of the office stock? For NYC, we observe $20 billion in lease revenue in the CompStak data and the ratio of office value to lease revenue is 8.76 based on our model. Hence, the value of the NYC office properties in our dataset is $175 billion.[2] The short-term value reduction of 33% amounts to $57.7 billion, the longer-term reduction of 28% amounts to $49 billion. Extrapolating to all properties in the U.S. in our dataset, the $72 billion annual leasing revenue results in a $631 billion office value before the pandemic using the same 8.76 value/lease revenue ratio. We estimate that pandemic-related disruptions around remote work have lowered the value of office buildings observed in our dataset by $208 billion in the short run (33%) and by $177 billion in the long-run

[2]This number is very close to the $172.3 billion estimate in an October 2021 report New York State Comptroller's office.

(28%). These estimates understate the value destruction of the overall U.S. office stock since our CompStak data do not cover the universe of commercial leases. We underestimate lease revenues by a factor of about 2.8.[3] The total decline in commercial office valuation might be, as a consequence, around $586 billion in the short-run and $498 billion in the long-run.

Related Literature Our work relates to three literatures. One strain of research has focused on identifying disruptive technological shocks to asset prices. A specific concern in this literature has been the problem of stranded assets: whether innovation or novel risks such as climate change have the potential to transform existing assets into liabilities, with consequences for the creative destruction of economic growth (Barnett, Brock and Hansen, 2020; Gârleanu, Kogan and Panageas, 2012; Kogan and Papanikolaou, 2014). We contribute to this literature by documenting a novel form of disruptive technology shock in the form of remote work, and highlight its consequences for urban commercial assets.

We also relate closely to the literature on the impact of remote work on real estate. Rosenthal, Strange and Urrego (2021) documents a decline in the commercial rent gradient in the city center and transit cities as compared to car-oriented cities with COVID-19. Barrero, Bloom and Davis (2021) use survey data to 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. We also contribute to recent research which studies the economic impact of COVID-19. Gupta, Mittal, Peeters and Nieuwerburgh (2021) studies the impact of work from home on residential real estate prices in urban and suburban areas of top 30 MSAs. Cohen, Friedt and Lautier (2020) shows changes in real estate prices in New York City due to COVID-19. Brueckner, Kahn and Lin (2021) and Delventhal, Kwon and Parkhomenko (2021) study the impact of working from home on cities. Our paper uses micro lease-level data to document changes in commercial real estate markets with a rise in work from home, and proposes a work from home risk factor.

[3] We have 1,906 million square feet of active leases in our dataset in February 2020, just prior to the onset of the pandemic. According to Cushman & Wakefield, the U.S office inventory at the end of 2019 was 5,375 million square feet. The ratio of these two numbers is 2.82.

Finally, our work relates to literature examining commercial real estate as an asset class. A key contribution of our paper is developing a tractable yet rich model of commercial building valuation. Cvijanović, Milcheva and van de Minne (2021) studies market segmentation by investor characteristics in commercial real estate. Our paper contributes to this literature by proposing a methodology with broad applicability to study valuation in different contexts.

The rest of the paper is organized as follows. Section 2 overviews changes in the office 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 describes our REIT financial data in more detail. Appendix C provides model derivations. Appendix **??** estimates changes to future cash flows through analyst expectations and lease renewal models. Appendix D reports additional results from the model.

2 The Office Market During the Pandemic

2.1 Data

In comparison to other real estate markets, for instance in residential real estate, the market for commercial office buildings is comparatively opaque. We combine data from both public and private markets in order to make progress in understanding valuation of the entire sector in light of disruptions introduced by the coronavirus pandemic and 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–December 2021. Data coverage improves in the first part of the sample and stabilizes around 2015.

Each lease contains information on the lease, the building, and the tenant. Lease characteristics are: 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), other lease options. Building characteristics include: building location, building class (A, B, or C), building age, sub-market, market. Tenant characteristics include: tenant name, tenant industry (SIC and NAICS code), tenant employees, 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, contract features, and to estimate a lease renewal model that takes tenant characteristics into account.

In public markets, we obtain the list of office REITS as the constituents of the National Association of Real Estate Investment Trust (NAREIT) office index for the period 2019–2021.[4]. Using this list of REITs, we develop a novel data set of annual REIT financials from the 10-K filings with the SEC. We hand-collect lease revenue including tenant reimbursements, total revenue, funds from operation (FFO), net rentable square feet, and occupancy rate. We connect this to REIT earnings forecast data from I/B/E/S.

Finally, 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.

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.

[4]The constituent list can be found here: `https://www.reit.com/data-research/reit-indexes/monthly-index-constituents` A list of REITs we focus on can be found in Appendix Table 7.

The total value of annualized leasing revenue exceeded $72 billion (in December 2021 dollars) prior to the pandemic in January 2020. Total leasing revenue then experienced a substantial decline, falling 8.1% by December 2021 to about $66 billion (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 space decisions.

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

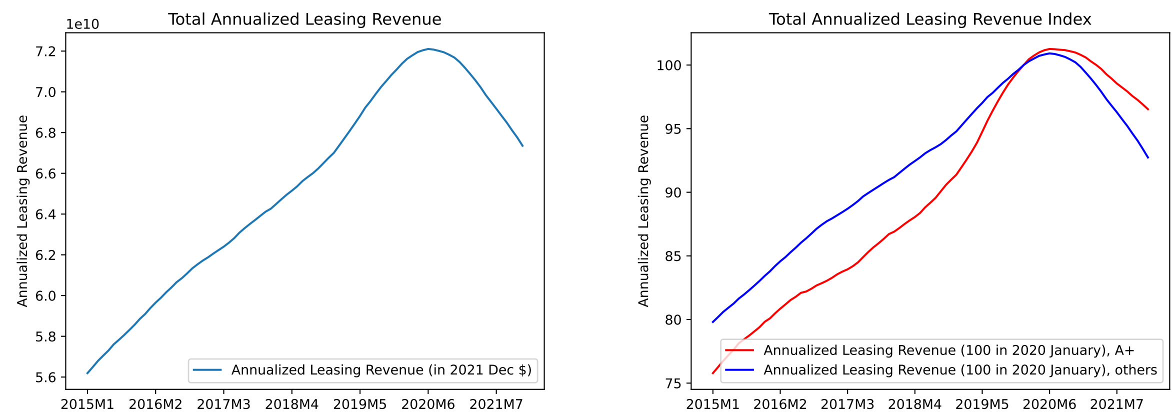
While we observe contractual pricing terms in the CompStak data, lease terms require some discussion. We focus on net effective rents (NER), which augment the standard contract rent schedule (a rent for each month over the course of the lease) with additional provisions including rent concessions (free rent) as well as tenant improvements (work paid for by the landlord). The resulting NER reflects the effective rent earned per month by the landlord, and is the most relevant object in understanding changing market rent dynamics. Annualized net effective rents on *in-force* leases continue to go up throughout the pandemic. This reflects the fact that most leases that are in-force during the pandemic were signed before the pandemic and may have had built-in rent escalation clauses. We 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 contrast, the quantity of in-force leases (in square feet) fell dramatically during the pandemic (Panel C). The decline is 10.2% between January 2020 and December 2021. This decline reflects both difficulties in filling vacant space with new tenants and lack of lease renewals (or partial renewals) by existing tenants whose lease is up for renewal. This suggests that understanding the quantity dimension is of utmost importance when it comes to understanding shocks to pandemic cash flows.

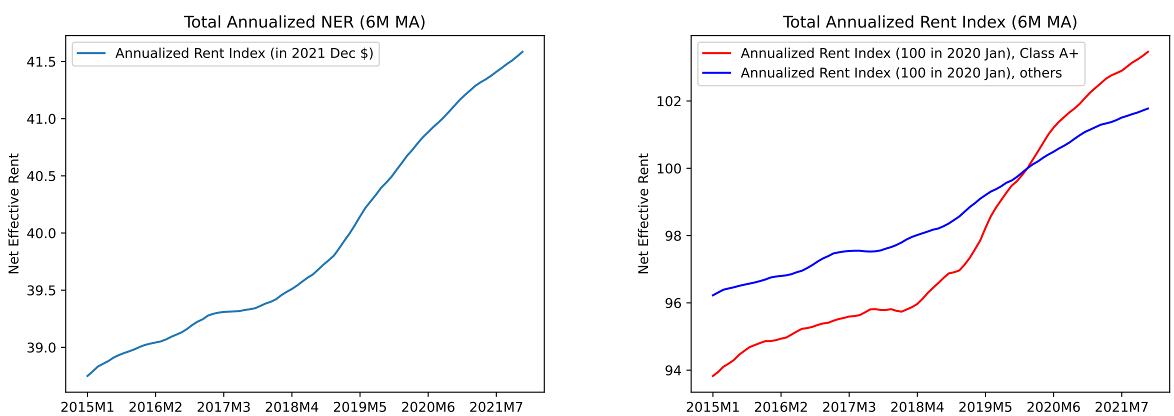
We also observe that this decrease in current lease revenue is felt most strongly for lower than for higher quality office space. To measure high quality buildings, we define "A+"

Figure 1: Current Office Lease Revenues

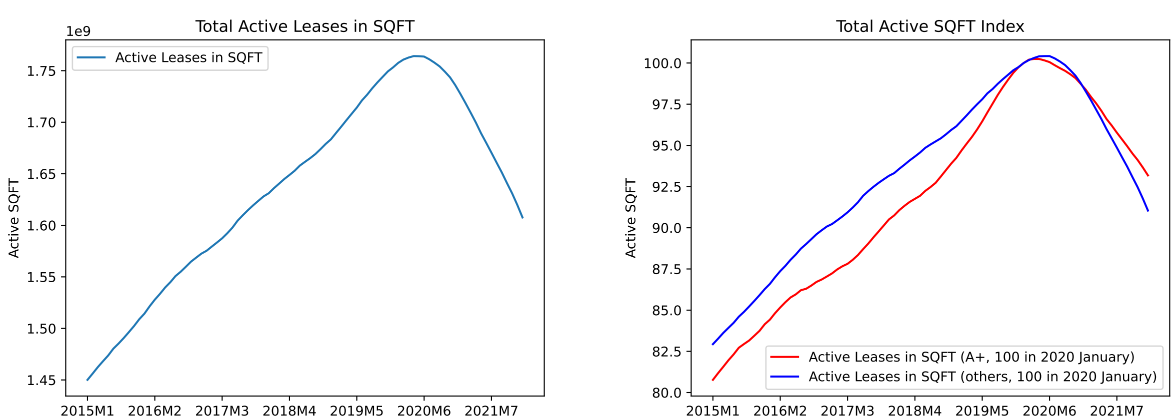
Panel A: Total Lease Revenue on In-force Contracts



Panel B: Average Rent on In-force Contracts



Panel C: Quantity of In-force Contracts



properties by isolating leases that are in the top ten percent of net effective rents in each quarter and sub-market among all properties that are ranked as Class A by Compstak. We categorize all buildings that ever have a lease in this top decile as A+, and plot trends separately by office quality in the right panels of Figure 1, normalizing trends for Class A+ and other buildings at 100 in January of 2020. We find that rent increases are much stronger for Class A+ buildings after 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 revenue sees less of a decline in Class A+ buildings (Panel A). Concretely, leasing revenues fall by 5.2% for A+ versus by 9.2% for the rest of the office universe (classes A-, B, and C).[5]

We observe even stronger evidence for differing trends across office space by quality in Figure 2, which focuses on New York City and Texas, as representative examples of both major and non-major commercial real estate markets. Panels A and B display changes in net effective rents per sf on newly-signed leases for properties. The left panels define A+ properties as before. The right panels entertain an alternative definition based on building age to identify trends in rents across building quality: 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.

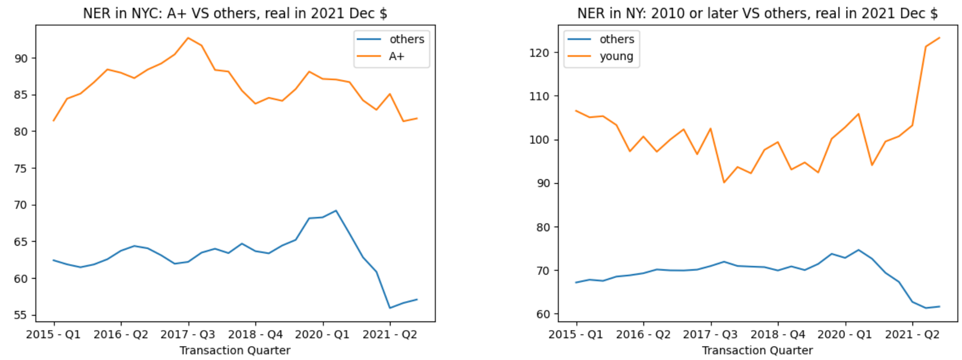
2.3 Physical Occupancy, Lease Expiration Schedules, and Contractual Vacancy

We continue with a descriptive summary of office market dynamics through the pandemic to illustrate the extraordinary shock experienced in this market. In Figure 3 we highlight the key shift we focus on our paper: the sudden drop in physical office presence for white-collar

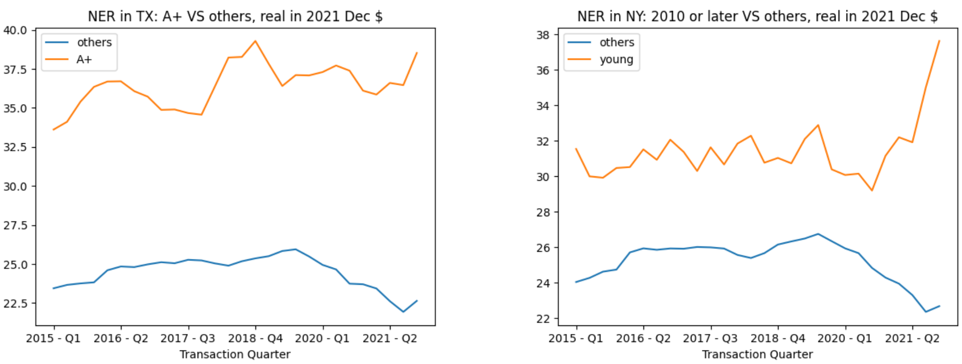
[5]These numbers are the actual declines, not the six-month moving averages plotted in the graph. These numbers average to the 8.1% number for the overall office stock reported earlier.

Figure 2: Changes in Office Rents and Occupancy

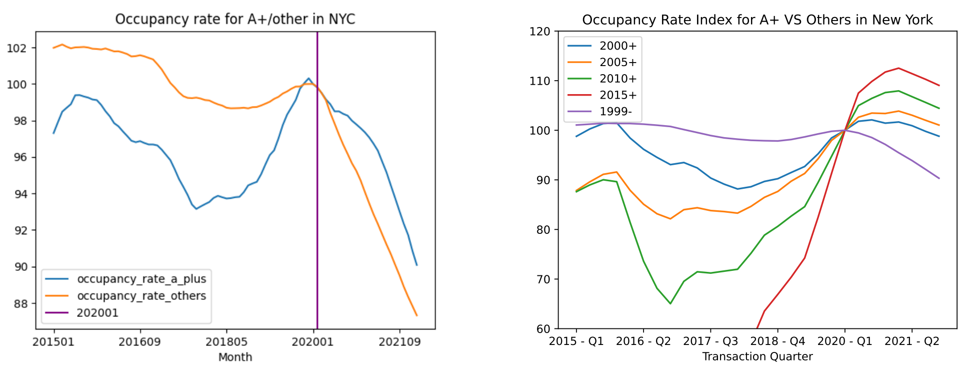
Panel A: Net Effective Rent for A+ and Young vs. Others in NYC



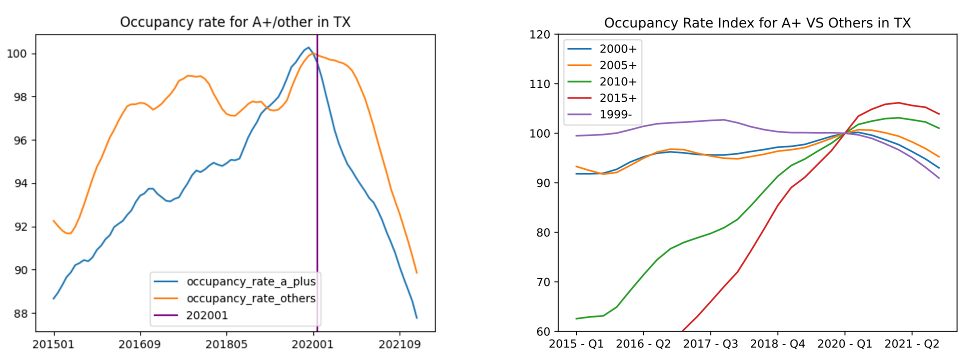
Panel B: Net Effective Rent for A+ and Young vs. Others in Texas



Panel C: Occupancy Rates for A+ and Young vs. Others in NYC



Panel D: Occupancy Rates for A+ and Young vs. Others in Texas



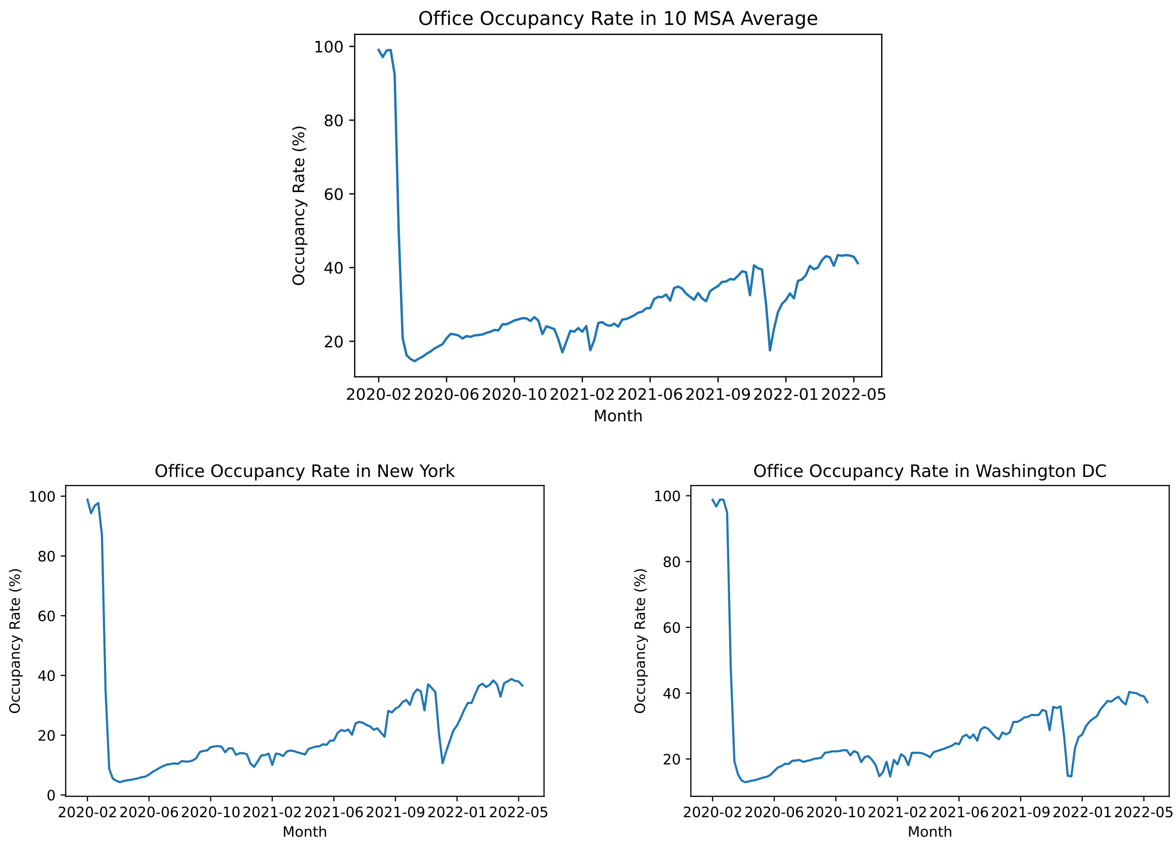
workers. Physical office occupancy is measured from turnstile data provided by Kastle.[6] Over the course of the pandemic, about 70% of college-educated workers did some or all of their work from home. In the initial wave of the pandemic, physical office occupancy rates fell to just 20%. Average occupancy recovered to about 30% among the top-10 largest office markets 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 50%, before falling sharply due to the rise of the Omicron variant at the end of 2021. The latest data as of May 2022 show a 50% occupancy rate among the largest 10 office markets. Occupancy rates are lower in several large metros such as New York City and Washington DC highlighted in the other panels of this figure. Occupancy stands at 38.8% in NY MSA, 40.0% in DC, and 34.6% in SF on May 11, 2022. With two years of remote work experience, many employers and employees have formed new habits and expectations, which may permanently affect where work is done.

Surprising many observers, these large drops in physical occupancy did not translate into large immediate drops in commercial office cash flows. One key reason for the delayed 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. Of all in-force leases as of the end of December 2019, only about 35% 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 question in our analysis.

Despite the limited number of tenants that have seen lease expirations so far, we observe drastically higher vacancy rates reflecting lease exits among that sample. The office vacancy rate in Manhattan, the country's largest office market, was at a 30-year high of 20.4% in the last quarter of 2021. Panels C and D of Figure 2 plot occupancy rates for NYC and Texas. The

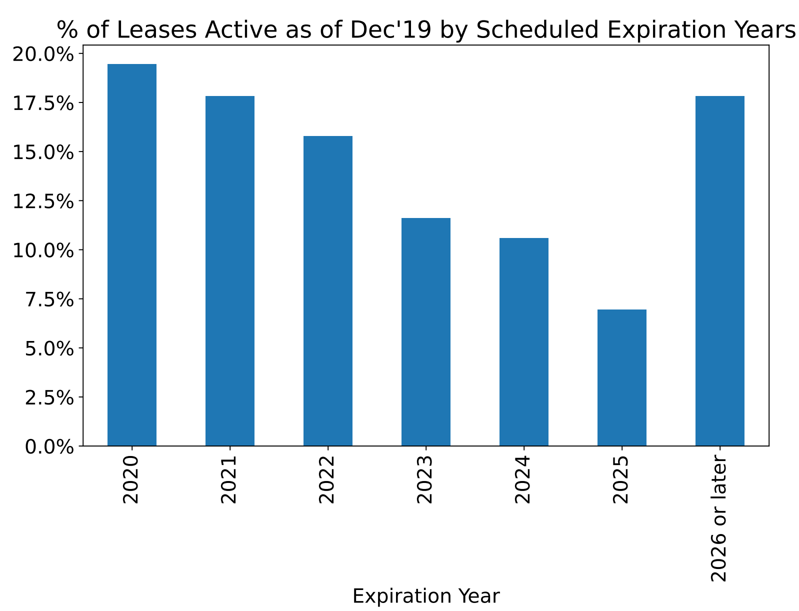
[6]The Kastle data cover more than 2,600 buildings in 138 cities.

Figure 3: Physical Office Occupancy



Source: Kastle turnstile data

Figure 4: Lease Expiration Schedule



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 Leasing Quantities and Prices

Pandemic Impact on Lease Quantities

We next turn, using CompStak data, 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, expressed in square feet. We also break down this total into major markets and non-major markets.[7]

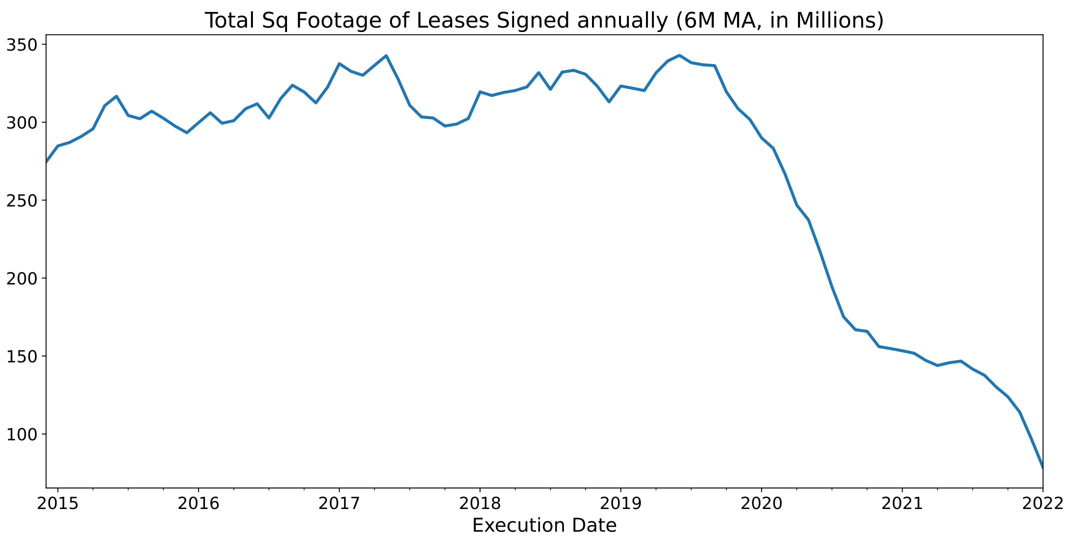
We observe large and dramatic decreases in the quantity of new leases signed, sometimes called absorption in the industry, across both sets of markets in Figure 5. The volume of newly signed leases fell from over 300 million sf per year before the pandemic to about 100 million sf per year over the most recent six months. This indicates a massive drop in office demand from tenants who are actively making space decisions.

Pandemic Impact on Lease Duration

Even if 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 to account for almost half of our sample, while the share of leases with durations more than seven years decreased meaningfully. The dramatic shortening of lease durations 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 expirations from two channels: the pre-scheduled expiration of long-term leases, as well as the expiration of short-term leases signed during the pandemic.

[7] 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



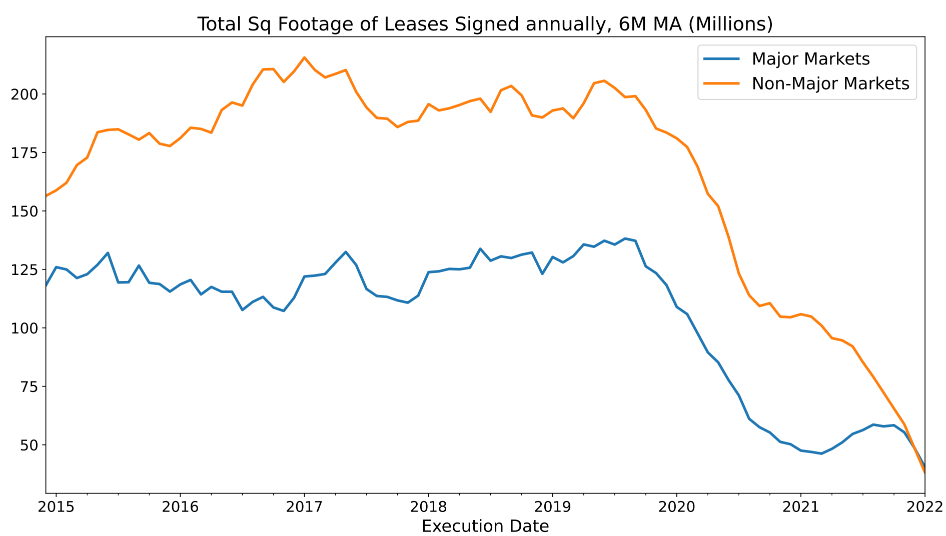
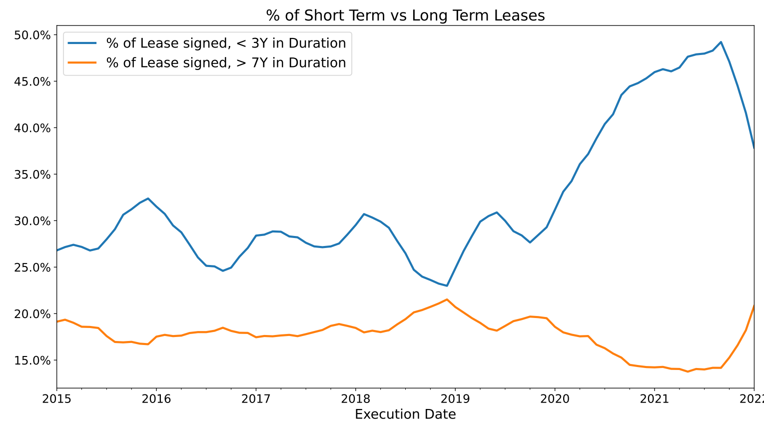


Figure 6: Lease Duration Changes



Pandemic Impact on Rents

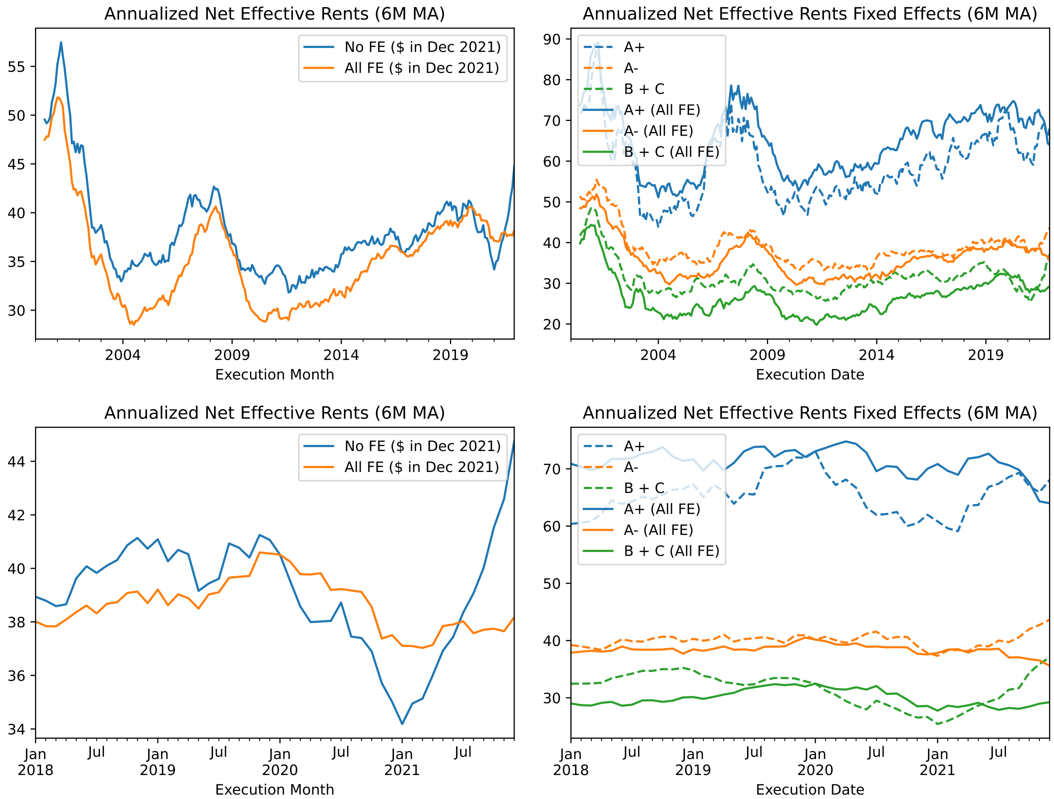
We next explore the dynamics of net effective rents on new leases. We compute the square-foot weighted average NER and again express the rent in 2021 dollars. Figure 7 shows large changes in real NERs on new leases signed over the course of the pandemic. Panel A is for all markets and Panel B is for New York City. We provide both a longer-term perspective in the top row and zoom in on the psot-2018 period in the bottom row of each panel. Between January 2020 and December 2020, the NER fell by 9.9% in real terms nationally (blue line). From December 2020 until September 2021, the NER on newly-signed leases experiences 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 where 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 fixed effects, geographical fixed effects (state or major/non-major market), or both. Once fixed effects removed, the national decline in NER in 2020 is weaker and the rebound in 2021 disappears. That is, it is revealed to be a spatial composition effect.

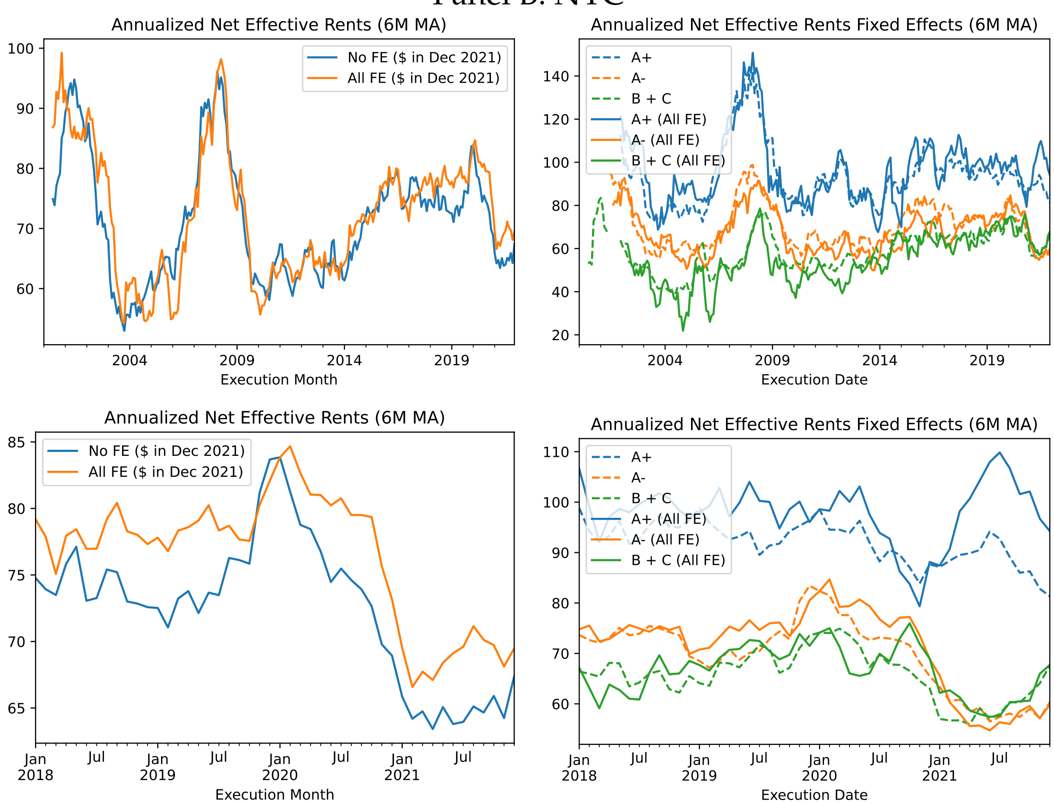
In NYC, the NER decline on new leases in 2020 is sharper at 24%, and not sensitive to tenant of sub-market fixed effects. There is little evidence of a NER rebound in 2022.

Figure 7: Net Effective Rent During Pandemic

Panel A: National



Panel B: NYC



Source: CompStak. All FE includes state, major/non-major market, industry and renewal FEs.

The right panels break down the market-wide NER dynamics by quality segment: A+, A- (all other class A), and B+C. We focus on the solid lines, which remove fixed effects. Nationally, A+ rents on new leases show resilience during the pandemic. In NYC, A+ rents on new leases fall by more in 2020 but rebound more sharply in 2021 than the remaining assets.

2.5 Connecting Remote Work and Office Demand

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 as a consequence, 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 shocks to office demand as a consequence.

In order to connect the changes in office demand to shifts in remote work specifically over the course of the pandemic, 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. We do so by searching for phrases in the text of the job listing that suggest that the job is fully remote.

We then compare the fraction of job listings that are remote with the change in office demand by that same firm. The change in office demand is measured as the percentage change in active lease space (in sf) normalized by employment growth over the course of the pandemic. Tenants that do not renew leases that come up for renewal during the pandemic, that renew and take less space, or that do not expand space in proportion to their total number of employees have a low value for change in office demand. We are able to compile this data for 135 large tenants in our Compstak database.

Table 1 reports the results of a regression of the change in office demand on the fraction of remote-job postings, 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 significantly negative relationship at all horizons. Our results suggest that firms that have greater remote demand in job listings are less likely to demand office space, consistent with the idea that durable technological shifts are driving changing demand for office space.

Table 1: 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	-0.0106	-0.0156
	(-0.61)	(-0.52)	(-0.77)
Observations	135	135	135
R^2	0.042	0.044	0.030

t statistics in parentheses.

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

Note: The dependent variable, Δ Space, is constructed from Compstak and defined as the SQFT of leases executed post-pandemic minus the positive part of the difference between SQFT of leases expired post-pandemic and SQFT of leases commenced post-pandemic, and normalized by pre-pandemic active SQFT. 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 Feb 2022. More specifically, we look at Dec 2021 to Feb 2022, Jan 2021 to Feb 2022 and Jan 2020 to Feb 2022 and check the ratio of tenants' remote jobs over their total job postings.

3 Office Valuation Model

How do the 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. Like any valuation, this comes down to cash flows and discount rates. Conceptually, the value of a building (or portfolio of buildings or market) is the expected present discounted value of rent revenues Rev_{t+j} minus expenditures $Cost_{t+j}$:

$$\begin{aligned} V_t &= E_t\left[\sum_{j=1}^{\infty} M_{t,t+j}\left(Rev_{t+j} - Cost_{t+j}\right)\right] = E_t\left[\sum_{j=1}^{\infty} M_{t,t+j} Rev_{t+j}\right] - E_t\left[\sum_{j=1}^{\infty} M_{t,t+j} Cost_{t+j}\right] \\ &= V_t^R - V_t^C \end{aligned} \tag{2}$$

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 that 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 when they have different lease structures in place. The leases are finite, but there is rental revenue after the leases mature. After some initial vacancy and some initial 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. 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 market, which is a portfolio of buildings. The full derivation of the model is in Appendix C. This model can be used to value a building in any sector or location. Section 3.3 describes the calibration of the model, which will focus on the office market in New York City.

3.1 Modeling Revenues

Leases are long-term. A lease comes 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 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 sf) 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 $\overline{Q}_t$ is the total size of the building/market then $Q_t^V = \overline{Q}_t - Q_t^O$. Then the law of motion for occupied space in a building/market is:

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

The first term denotes the space that was occupied at the end of last period and is not up for renewal.

The second term denotes the space that was up for renewal and is renewed. Here, $0 \leq s_{t+1}^O(z') \leq 1$ is the share of office space that was up for renewal that 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 $t+1$. This 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 that is renewed conditional on renewal). The second term captures lease renewals for the same or for less space.

The third term denotes space that was vacant at the end of last term and is being newly rented. The stochastic process $0 \leq s^V_{t+1}(z')$ is the share of office space that was vacant that is being newly rented out in period $t+1$ if period $t+1$ is in regime z'. This term includes the part of lease expansions (renewals for more space) that exceeds the original space. This share is not bounded from above by 1, to allow for growth in a building/market due to changes in the supply (renovation of a building that adds floorspace/new construction in a market). 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 regime the model is in:

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

We define the scaled state variable $\hat{Q}^O_t$:

$$\hat{Q}^O_t = \frac{Q^O_t}{\overline{Q}_t}$$

The law of motion for the scaled state variable is:

$$\hat{Q}^O_{t+1}(\hat{Q}^O_t, z') = \min\left\{ \frac{\hat{Q}^O_t(1-\chi) + \hat{Q}^O_t \chi s^O_{t+1}(z') + (1-\hat{Q}^O_t) s^V_{t+1}(z')}{1+\eta_{t+1}(z')}, 1 \right\} \tag{3}$$

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

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

where R^O_t is the average net effective rent per square foot on existing leases and R^m_{t+1} is the market's net effective rent (NER) per square foot on newly executed leases. The net effective rent incorporates concessions (free rent) and tenant improvements. We assume that the 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 share of outstanding leases that was 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: it's 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:

$$\hat{R}_{t+1}^O(\hat{R}_t^O, z') = \frac{1-\chi}{1+\epsilon_{t+1}(z')} \hat{R}_t^O + \chi \tag{4}$$

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 rent revenue scaled by last period's potential rent (rent revenue based on full occupancy at the prevailing market rent):

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

Recall the expected 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:

$$\hat{V}_t^R(\hat{Q}_t^O, \hat{R}_t^O, z) = \sum_{z'} \pi(z'|z) M(z'|z) \left\{\widehat{Rev}_{t+1}(\hat{Q}_t^O, \hat{R}_t^O, z') + (1+\eta(z'))(1+\epsilon(z'))\hat{V}_{t+1}^R(\hat{Q}_{t+1}^O, \hat{R}_{t+1}^O, z')\right\} \tag{5}$$

subject to the laws of motion for the scaled state variables (3) and (4).

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, denoted as C_t^{var}.

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.

Building costs are:

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

We scale costs by lagged potential rent:

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

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

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

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:

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

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

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

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

$$\hat{V}_t^C(\hat{Q}_t^O, z) = \sum_{z'} \pi(z'|z) M(z'|z) \left\{ \widehat{Cost}_{t+1}(\hat{Q}_t^O, z') + (1+\eta(z'))(1+\epsilon(z'))\hat{V}_{t+1}^C(\hat{Q}_{t+1}^O, z') \right\} \tag{6}$$

subject to the law of motion for the scaled state variable in (3).

The Bellman equations (5) and (6) have closed-form solutions spelled out in Appendix C.

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. Since risk and return are likely to vary across space, we focus here on New York City. One key parameter will be identified off the A+ segment of the NYC office market, so we also need a calibration for that segment of the NYC office market.

3.3.1 States and State Transition Probabilities

The state variable z follows a Markov Chain. Before Covid-19, it takes on two values: expansion (E) and recession (R). Starting in 2020, there are four states of the world for z: expansion, contraction, 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. Equivalently, there are always four states of the world but the last two occurred with zero probability before 2020.[8]

The model is calibrated at 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 matrices are assumed to

[8]Arguably there was a small amount of remote work even before 2020, around 5% by some estimates. We abstract from this baseline level of remote work.

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 typical length of a recession. Recessions are shorter-lived than expansions. This pins down the 2×2 matrix $\pi^{BC}(z'|z)$.

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

The WFH transition matrix is a key object in our valuation exercise. We set the probability of entering in the WFH state from the no-WFH state equal to $\mathbf{q} = 5\%$ capture the fact that remote work existed before 2020 but that a transition to mass adoption of remote work was highly unlikely before 2020. The second parameter is the probability of remaining in the WFH state conditional on having entered it, which we label $\mathbf{p}$. The latter governs the persistence of remote work, and it is the key parameter of interest in the paper. We will infer the value of $\mathbf{p}$ from the observed change in class-A+ office valuations at the onset of Covid, as inferred from office REIT data, and perform robustness with respect to this parameter. As explained in detail below, this calibration delivers $\mathbf{p} = 0.868$. These two parameters pin down $\pi^{WFH}(z'|z)$:

$$\pi_{WFH} = \begin{array}{r} \\ \text{No WFH} \\ WFH \end{array} \begin{array}{c} \begin{array}{cc} \text{No WFH} & WFH \end{array} \\ \begin{bmatrix} 1-q & q \\ 1-p & p \end{bmatrix} \end{array} = \begin{array}{r} \\ \text{No WFH} \\ WFH \end{array} \begin{array}{c} \begin{array}{cc} \text{No WFH} & WFH \end{array} \\ \begin{bmatrix} 0.95 & 0.05 \\ 0.132 & 0.868 \end{bmatrix} \end{array}$$

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 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 $M^{BC}(z'|z)$:

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

The model matches the observed long-term average real risk-free rate of 1.5%. The model 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 expected equity return and the equity risk premium are substantially higher in recessions (13.8%) than in expansions (6.9%).

The SDF that governs the risk associated with working from home $M^{WFH}(z'|z)$ is calculated by matching 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 call this portfolio the WFH factor. Appendix A.2 contains the details of the WFH factor construction. In order to analyze how remote work is priced, i.e., what the risk premium is associated with WFH risk, we look at the average return on the WFH factor in the period before the pandemic, namely January 2015–January 2020. This avoids confusing realized with expected returns.[9] Since the WFH factor may have exposure to the overall stock market and bond market, we are interested in the excess return λ^{wfh} after removing compensation for stock and bond market risk exposure:

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

where β^{mkt} and β^{bond} are calculated from returns during the pre-pandemic period. Appendix A.4 shows that λ^{wfh} is -7% and Appendix A.5 shows that the equity and bond risk premia are λ^{mkt} and λ^{bond} are 7.81% and 2.92% in the data.

The return during the transition from no-WFH to the WHF state, $Ret^{wfh}(z' = WFH|z = \text{No WFH})$, is matched to the realized returns on the working from home factor between January 2020 and December 2020.

We normalize $M^{WFH}(\text{No WFH}|\text{No WFH}) = 1$. Pricing the WFH risk factor return correctly for $z = \text{No WFH}$ pins down $M^{WFH}(WFH|\text{No WFH})$, given the normalization:

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

We set the second row of M^{WFH} for for $z = \text{No WFH}$ equal to the first row, given that we do not have enough data to observe average returns on the WFH factor conditional on being in the WFH state. Finally, since we want the risk-free rate to be fully determined by $M^{BC}(z'|z)$ and unaffected by M^{WFH}, we scale M^{WFH} such that $E[M^{WFH}]$ is equal to 1 for each state z:

$$M^{WFH,unscaled} = \begin{array}{r} \\ \text{No WFH} \\ WFH \end{array}\!\!\begin{array}{c} \begin{array}{cc} \text{No WFH} & WFH \end{array} \\ \begin{bmatrix} 1 & 1.696 \\ 1 & 1.696 \end{bmatrix} \end{array}, \quad M^{WFH} = \begin{array}{r} \\ \text{No WFH} \\ WFH \end{array}\!\!\begin{array}{c} \begin{array}{cc} \text{No WFH} & WFH \end{array} \\ \begin{bmatrix} 0.966 & 1.639 \\ 0.623 & 1.057 \end{bmatrix} \end{array}$$

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.

[9] Indeed, realized and expected returns move in opposite direction when the economy transitions from the no-WFH to the WFH state.

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.

We set the lease expiration parameter at $\chi = 0.14$. This delivers a lease duration of 7.09 years, matching the CompStak average office lease term in the New York City data. Table 2 lists the remaining parameters, which vary by state.

Table 2: Calibration for NYC

Variable	Symbol	E	R	WFHE	WFHR
Market NER growth	ϵ	0.026	-0.044	0.000	-0.050
Supply growth	η	-0.006	-0.003	-0.016	-0.013
Lease renewal share	s^O	0.798	0.742	0.622	0.579
New leasing share	s^V	0.189	0.095	0.146	0.073
Fixed cost/rent ratio	c^{fix}	0.200	0.200	0.200	0.200
Variable cost/rent ratio	c^{var}	0.230	0.230	0.230	0.230
Leasing commission new	LC^N	0.300	0.300	0.240	0.240
Leasing commission renewals	LC^R	0.150	0.150	0.120	0.120

Market NER growth ϵ in expansions and recessions comes from the January 2000 to February 2020 CompStak data. NER growth is strongly pro-cyclical. Market NER growth is assumed to be lower in the remote work state. Indeed, market NER growth in the CompStak data was -10% from March 2020 to February 2021 (a WFH-R episode), and -4% from March 2021 to January 2022 (a WFH-E). We only have one annual observation for NER growth for each of the two WFH states, and those observations are for a specific transition. Hence, we cannot simply assume that those are the conditional means of NER growth in the WFH-R and WFH-E states.[10] We choose higher values than the realized ones that (i) satisfy $\epsilon(E) > \epsilon(WFH-E) > \epsilon(R) > \epsilon(WFH-R)$, and (ii) are consistent with stable long-run NOI growth, given all other parameters.

Supply growth is modestly counter-cyclical because of the long construction lags for

[10] In fact, those realized values would lead to office valuations that trend to zero in the long run, which is implausible.

(NYC) office properties. The values for supply growth for expansion and recession periods are calculated from Compstak based on the year of construction of all office buildings in the data set. New construction is 1.2% in expansions and 1.5% in recessions. We naturally assume that supply growth falls in the remote work states compared to the no-WFH states. The values for supply growth in WFH-R and WFH-E periods are calculated by down-scaling E and R supply growth by 100 basis points.[11] Supply growth incorporates reconstruction and space conversion. We subtract a 1.8% depreciation rate from the new construction numbers to arrive at the net supply growth η reported in the table. This depreciation rate is (i) a realistic number, and (ii) results in long-run growth in potential gross rent of zero, keeping the model stationary.

The lease renewal share for existing leases that are up for renewal is pro-cyclical. It falls significantly in the WFH recession state. The new leasing share is strongly pro-cyclical and falls in WFH, specially in WFH recession. The parameters for expansion and recession states are chosen to deliver realistic vacancy rates for NYC, given all other parameters, via the law of motion of $\hat{Q}^O$.[12] The parameters s^O and s^V in the WFH states are assumed to be proportional to their no-WFH counterparts:

$$s^i_{z,wfh} = \delta \cdot s^i_z, \qquad\qquad z = E, R, \;\; i = O, V \tag{7}$$

δ is estimated to be 0.77 by plugging in equation 7 into the law of motion for $\hat{Q}^O$ and using the above estimates of s^O and s^V from no-WFH states.

These parameters generate conditional vacancy rates of 13.1% in E, 16.1% in R, 18.7% in WFH-E, and 21.5% in WFH-R. The model matches both the observed mean and volatility of the observed NYC office vacancy rate, as well as the jump to 20% vacancy rates in 2021.

[11] It is difficult to estimate these two parameters from data since we only have one annual observation of supply growth in each of the two WFH states, and since those realizations are conditional on a single transition from E to WFH-R, and from WFH-R to WFH-E, respectively.

[12] We estimate occupancy rates for NYC using Compstak data as follows. We first calculate the occupancy rate of all NYC buildings and A+ buildings in NYC. Then, we compute the ratio of these two time series. We multiply this ratio by the occupancy rate of the office sector from NAREIT. Given occupancy rates, we choose the parameters $s^O(E), s^O(R), s^V(E), s^V(R)$ in order to fit the law of motion for the occupancy rate in (3) in expansions and recessions.

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.

3.3.4 Office Cash Flows for A+ Properties in NYC

Next, we calibrate the model to A+ buildings of New York City. We look at the newly signed leases in NYC from 2015 onwards. For each submarket-quarter, we select the buildings with the top 10% of the most expensive (NER per sf) newly signed leases. We use these leases to get parameter estimates for the A+ NYC office sector.

χ is set to be 0.13 to match the average lease duration of 7.82 years of the Compstak A+ leases in NYC. The following Table 3 lists parameter estimates for the A+ case state by state: Similar to the NYC case, we choose the market NER growth and supply growth

Table 3: Calibration for NYC A+

Variable	Symbol	E	R	WFHE	WFHR
Market NER growth	ϵ	0.032	-0.042	0.025	-0.033
Supply growth	η	0.004	0.010	-0.006	0.000
Lease renewal share	s^O	0.919	0.769	0.760	0.636
New leasing share	s^V	0.168	0.177	0.139	0.147

parameters, but now only for the A+ buildings from Compstak. The η in the WFH states is again assumed to be 1% point lower than in the no-WFH states. The depreciation rate for these buildings is kept at 1.8%. The lease renewal share and new leasing share as estimated using the same methodology as for NYC as a whole, to match vacancy rates of office REITs sector; δ is estimated to be 0.83. The cost parameters are assumed to be the same as for the market as a whole.

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.[13] 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).

$$\left(\frac{\widehat{V}^{A+}(\widehat{Q}^O_{20}, \widehat{R}^O_{20}, WFHR)}{\widehat{V}^{A+}(\widehat{Q}^O_{19}, \widehat{R}^O_{19}, E)}\right)\left(\frac{\overline{Q}_{20}R^m_{20}}{\overline{Q}_{19}R^m_{19}}\right) + \left(\frac{\widehat{NOI}^{A+}(\widehat{Q}^O_{20}, \widehat{R}^O_{20}, WFHR)}{\widehat{V}^{A+}(\widehat{Q}^O_{19}, \widehat{R}^O_{19}, E)}\right) = (1 - 0.2275)$$

The magnitude of the value destruction crucially depends on the persistence of remote work $\mathbf{p}$. Figure 8 shows the realized return on A+ office in this transition, the left-hand side of the equation above, for a range of values of $\mathbf{p}$.[14] The graph shows that the office return in this transition varies strongly with $\mathbf{p}$, implying that this moment is well-suited to identify this parameter.

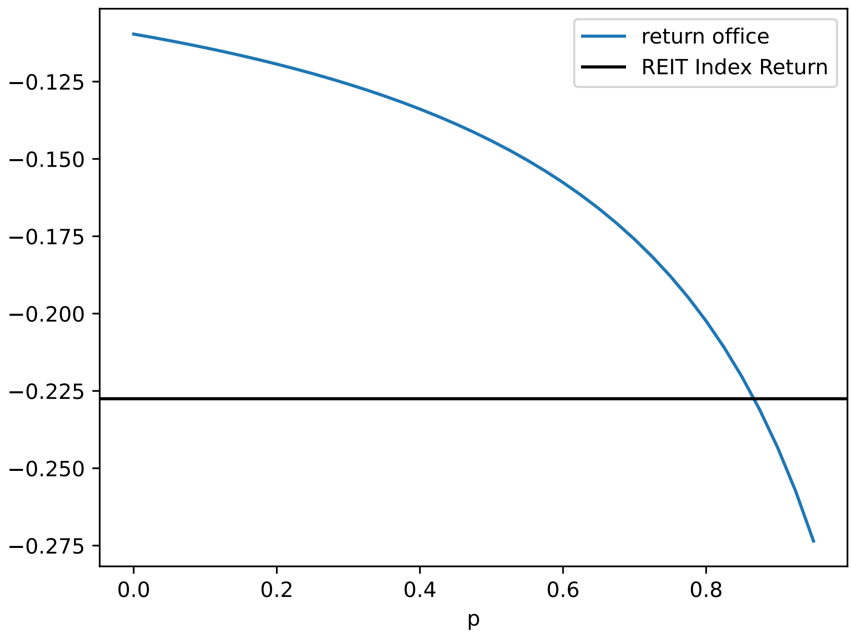
In order to pick the relevant point on this curve, we turn to the REIT data. REITS are well known to invest in class A+ office properties. Office REITS are also heavily skewed towards gateway markets like NYC. NYC-centric office REITs, namely SL Green, Vornado, and Empire State suffered a value-weighted decline of 36.16% between December 2019 and December 2020. After unlevering this equity return, the corresponding asset return was -22.75%.[15] The model matches this decline for a value of $\mathbf{p} = 0.868$. With this key parameter identified, we can return to the calibration for the full NYC office market and calculate the

[13] Given our assumptions on $M^{WFH}(\cdot|WFH)$ described above, the parameter $\mathbf{p}$ crucially affects the valuation of office buildings in the WFH state. It is best thought of as the risk-neutral probability of staying in the WFH state since there is not enough data to separately identify the physical probability of remaining in the WFH state and the corresponding state price.

[14] As the equation shows, this return depends also on the state pair $(\widehat{Q}^O_t, \widehat{R}^O_t)$ 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.

[15] Unlevering is done based on leverage ratio and cost of debt data from NAREIT.

Figure 8: Determining **p** by Matching Realized Return of A+ Market



change in its value due to remote work.

4 Main Results

4.1 Key Model Outcomes

Tables 4 presents the model solution for the "All NYC" office calibration. The model delivers a realistic unconditional average cap rate of 5.7% for the overall NYC office market. The cap rate is 6.4% in recessions and 5.5% in expansions. This is similar to the average hedonic-adjusted cap rate from Real Capital Analytics for Manhattan Office of 5.3% for 2001–19.[16] The RCA data also indicate higher cap rates in recessions (6.0% in 2001, 2008, 2009) than in expansions (5.2% for 2002–2007 and 2010–2019).

In a Gordon Growth Model with constant expected NOI growth rate g and a constant

[16] Cap rates were higher before 2001. Since our model's steady state pertains to a longer period than 2001–19, the slightly 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.

Table 4: Model Solution for NYC All Calibration

Statistic	Uncond	E	R	WFHE	WFHR
R_f	0.015	0.008	0.047	0.008	0.047
Equity $\mathbb{E}[Ret] - 1$	0.095	0.077	0.185	0.075	0.182
Equity RP = $\mathbb{E}[Ret] - 1 - R_f$	0.080	0.069	0.138	0.066	0.135
Cap rate	0.057	0.055	0.064	0.059	0.068
Office $\mathbb{E}[Ret] - 1$	0.057	0.044	0.123	0.044	0.120
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.043	0.035	0.076	0.036	0.073
$\mathbb{E}\left[g_t\right]$	-0.001	-0.003	0.037	-0.018	0.007
Vacancy rate $= 1 - \widehat{Q}^O$	0.151	0.131	0.161	0.187	0.215
$\widehat{\text{Rev}}$	0.814	0.817	0.842	0.795	0.806
$\widehat{\text{Cost}}$	0.415	0.421	0.414	0.403	0.395
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.399	0.395	0.429	0.392	0.411
$\widehat{V}^R$	13.625	14.281	12.740	12.835	11.509
$\widehat{V}^C$	6.483	6.843	5.923	6.087	5.342
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	7.142	7.438	6.817	6.748	6.168

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 5.7% and an office risk premium of 4.3%. This is naturally lower than the equity risk premium of 8.0% since an unlevered office property is much less risky that the aggregate stock market (which is a levered investment). The office risk premium is substantially higher in recessions (7.6%) than in expansions (3.5%).

Expected NOI growth is close to zero (-0.1% per year) unconditionally. This number is in real terms and already incorporates that the office stock depreciates at 1.8% per year (so it is 1.7% 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 higher in recessions than expansions by 3.0% points, and much higher in the remote work states, around 20%.

The last part of the table shows the value of the building, broken down into the PDV of revenues minus PDV of costs. The typical NYC office trades for a multiple of 7.14 times potential gross rent unconditionally according to our calibration. The average valuation ratio of office properties in the no-WFH expansion state of 7.44 is 20.6% higher than the value of 6.17 in the WFH-R state.

Figure 9 shows the valuation ratio for office $\widehat{V}$ conditional on expansion, recession, WFH-expansion and WFH-recession for NYC. 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 $\widehat{Q}^O$ and rent premium $\widehat{R}^O$.

4.2 Main Result: The Effect of WFH on Office Values

4.2.1 Entire Office Stock

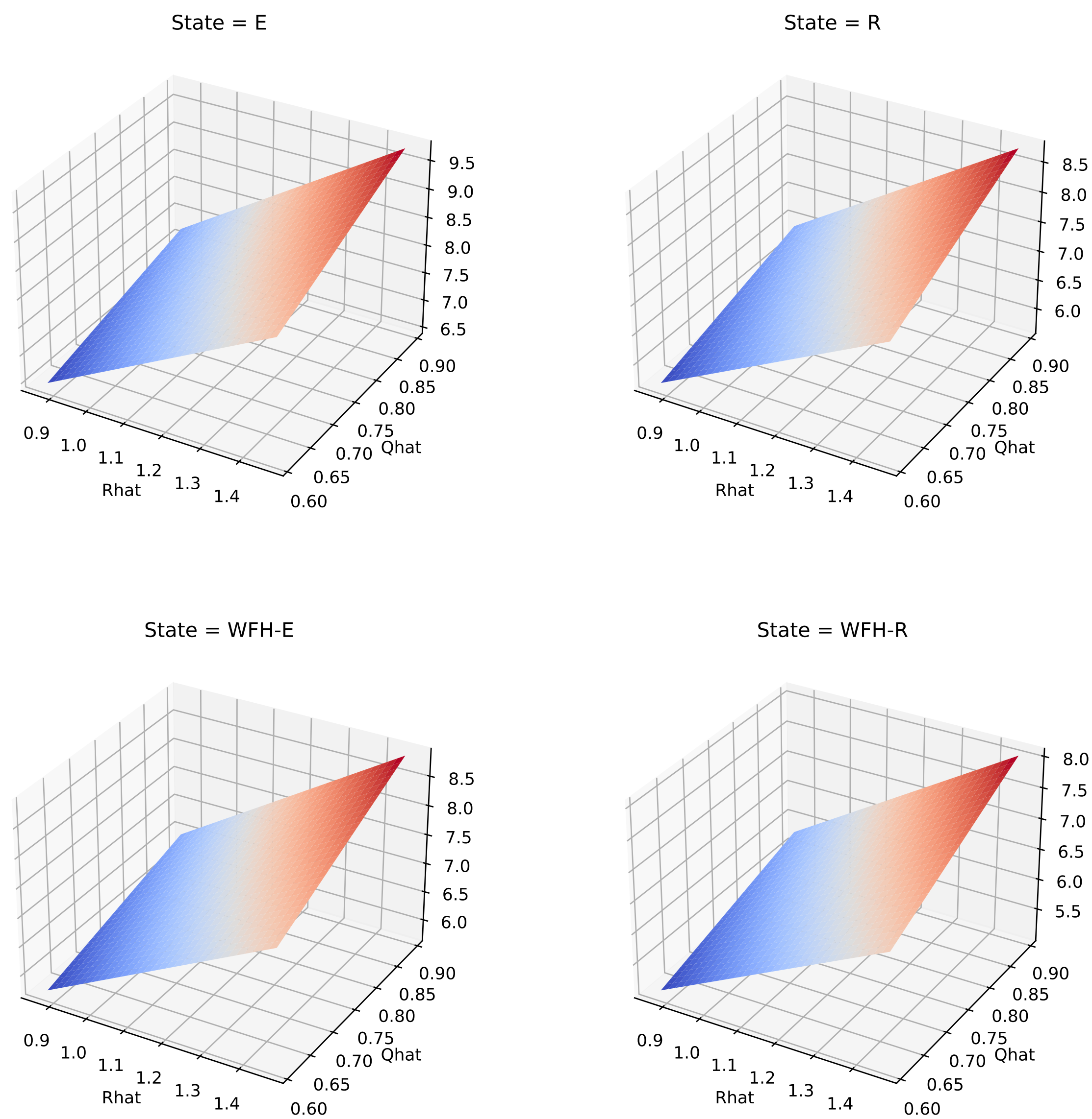
To assess the effect of remote work on office values, we let the economy undergo the same transition as the one we considered for A+ office when calibrating the parameter $\mathbf{p}$, namely from an expansion in the no-WFH state in 2019 to a WFH-R state in 2020. We feed in the observed history of expansions and recessions from 1926-2019 to arrive at the value for the endogenous state variables $(\widehat{Q}^O_{19}, \widehat{R}^O_{19})$ using the laws of motion for the states (3) and (4) under the "NYC All" calibration. The model captures the decade-long expansion before covid. We then apply the law of motion once more to obtain $(\widehat{Q}^O_{20}, \widehat{R}^O_{20})$ assuming the economy transitioned from E to WFH-R between 2019 and 2020.

The realized growth rate of potential gross rent in this transition is -6.23% in the model. The change in the scaled valuation ratio is -28.49%. Therefore, the overall value of the NYC office stock in this transition falls by 32.95%:

$$\left(\frac{\widehat{V}(\widehat{Q}^O_{20}, \widehat{R}^O_{20}, WFHR)}{\widehat{V}(\widehat{Q}^O_{19}, \widehat{R}^O_{19}, E)}\right)\left(\frac{\overline{Q}_{20}R^m_{20}}{\overline{Q}_{19}R^m_{19}}\right) = (1-28.49\%)\cdot(1-6.23\%) = (1-32.95\%)$$

Put differently, if the entire office stock of NYC had been publicly listed, its value would have

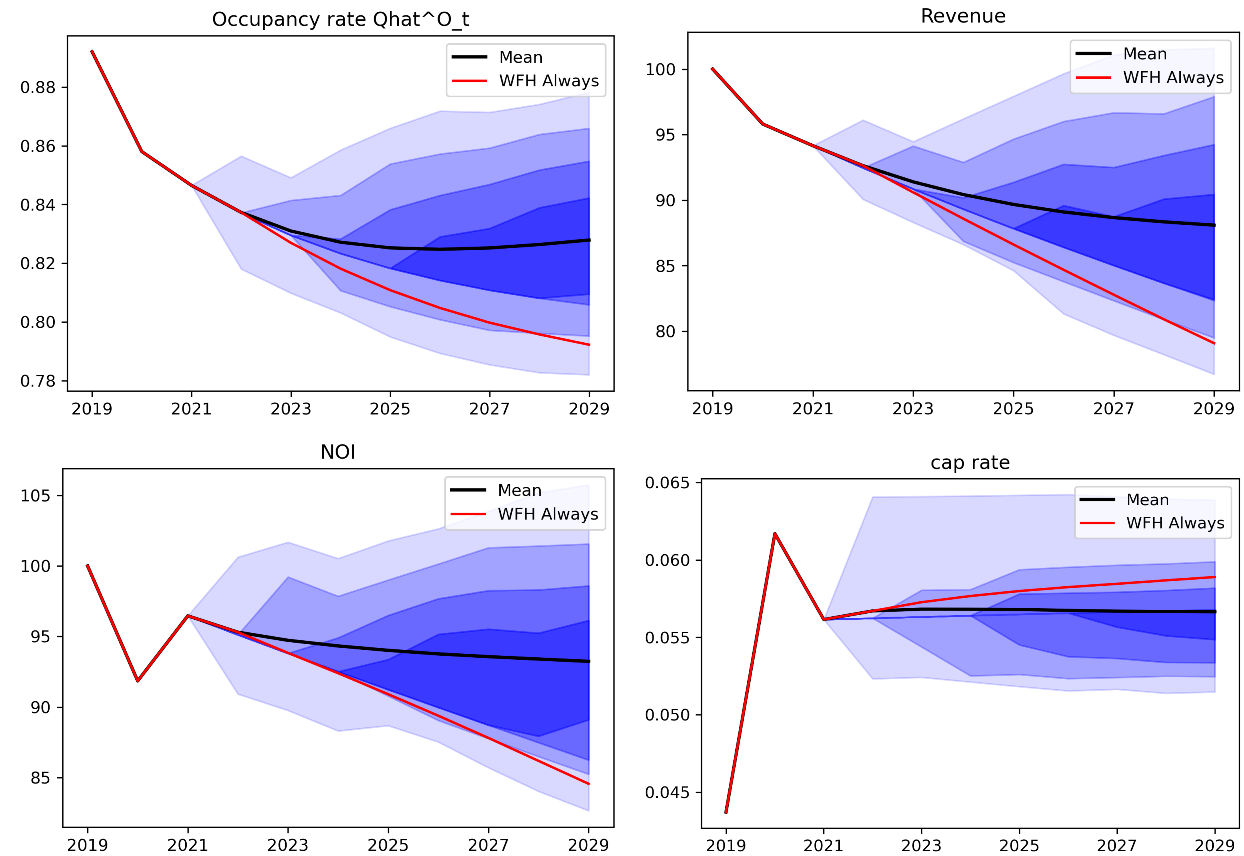
Figure 9: $\hat{V}$ for NYC All Market by States



fallen by 32.95% in 2020. This same decline was 25.44% 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. Since there are many possible paths for the evolution of the state, Figures 10 and 11 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 25% according to the model.

Figure 10: Key Moments Distributions, Normalized to 100 in Dec 2019



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

The top left panel of Figure 10 shows the occupancy rate dynamics from the model simulation. The model captures a substantial decline in occupancy from a high value of 89% in 2019. Since long-term leases continue to roll off and reprice at the new, lower market rates in 2022 and beyond, the decline in occupancy is protracted. Lease revenues, in the top right panel, reflect the protracted decline in occupancy and the repricing of existing leases. Lease revenues are down 12% by 2029 along the average path.[17] The bottom left panel shows that NOI falls by less since costs also decline in occupancy. The bottom right panel shows that office cap rates were below 4.5% in 2019 in the model, after a decade-long expansion that increased occupancy and rents. Cap rates then increase in 2020, fall modestly in 2021 as the economy shifts from recession to expansion, and then stabilize around 5.7% thereafter.

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 11. The graph illustrates a mean path that sees no recovery. Remote work is a near-permanent shock.[18] Ten years after the transition, office values remain at levels that are about 28% below the valuation in 2019. Along some sample paths, the economy returns to the no-WFH state and sees increases in occupancy rates ($\widehat{Q}^O$), 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 39.15% lower in 2029 than in 2019.

A second key message from the paper 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*.

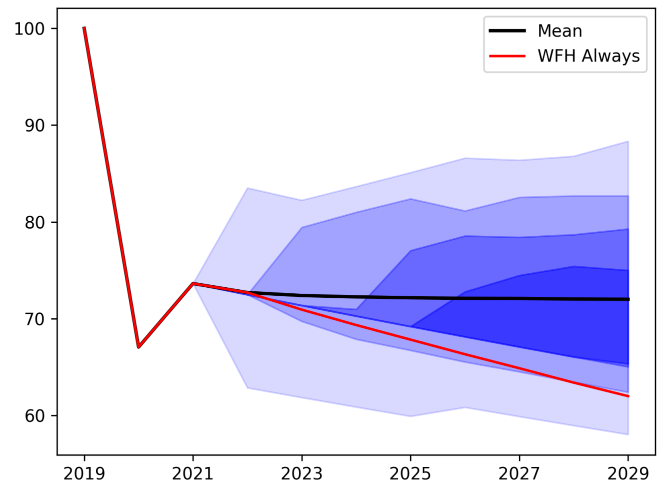
4.2.2 Flight To Quality

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. 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

[17] The model predicts a decline in actual lease revenues ($Q^O R^O$) of -5.85% between 2019 and 2021, which is close to the observed decline in lease revenues in the NYC Compstak data -6.73%.

[18] Combining the observed decline in lease revenue in NYC of -6.73% with the model-implied decline in the value/lease revenue ratio, we arrive at a change in office value of -27.06% between 2019–2021. This reflects a partial rebound from the -32.95% change in 2019–2020.

Figure 11: Office Valuation Distribution, Normalized to 100 in Dec 2019



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.

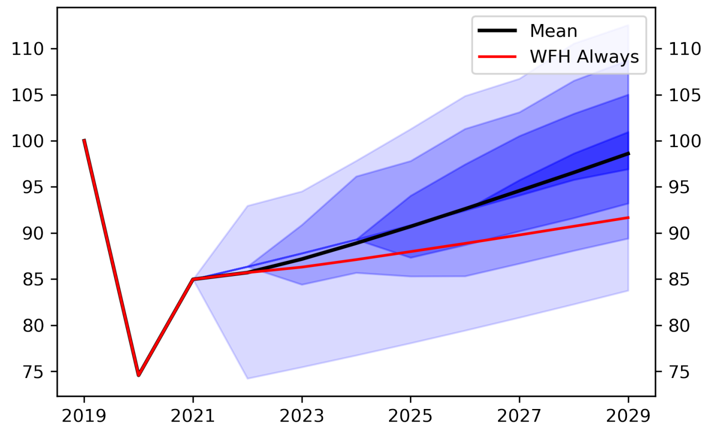
the lower risk of this segment.

Figure 12 revisits the transition graph for office values. It shows modestly smaller short-term value implications, as discussed before, and substantially smaller long-term value implications. The mean path has office values down by 1.5% 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 8.5%. This much stronger performance is due to the stronger rent growth for A+ in the WFH states, whose effects get magnified by the lower A+ office risk premium level 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. For example, the initial decline is -44% for A-/B/C compared to -33% for all office.

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 C.4 explains the procedure. Figure 13 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

Figure 12: Office Valuation Distribution, Normalized to 100 in Dec 2019



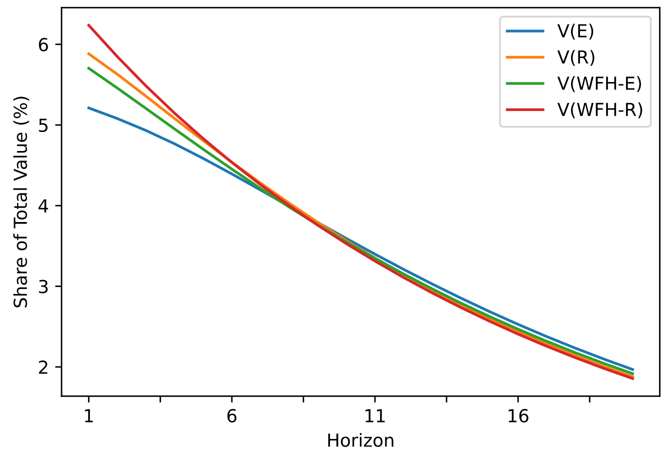
The graph shows the evolution of the A+ office value V for a transition from expansion in 2019 to WFH-R in 2020 and WFH-E in 2021. From 2022 onward, the state evolves stochastically. The shaded areas show percentiles of the distribution of simulated paths, with the darkest color indicating the 40-60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

sloping as cash flows in the near term are more valuable than cash flows in the far 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 WFH-R (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 due to 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 constellation is unusual, compared to the equity markets, where van Binsbergen, Brandt and Koijen (2012) find that the share of short-maturity equity cash flows falls in the mild recession of 2001, indicating an expected rebound in the near term, and stays flat in the deep recession of 2008, indicating a near-permanent shock to cash flows.

4.2.4 Robustness to Persistence of Remote Work

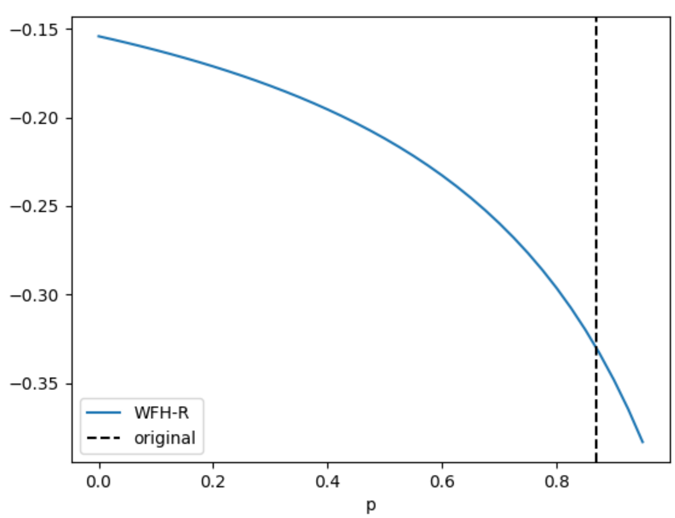
To assess how sensitive our headline value reduction number is, we explore alternative values for the key parameter $\mathbf{p}$. Figure 14 plots the difference in office values (V) between the

Figure 13: Decomposing Office Values by Horizon



model with no remote work in December 2019 and the model with remote work in December 2020. The vertical dashed line indicates our benchmark model with $\mathbf{p} = 0.868$, which produces a 32.95% valuation decline in the transition. This same decline is around 25.48% for a value of $\mathbf{p}$ that is half as large as our benchmark.

Figure 14: Change in Valuation with Different **p** for NYC All



5 Conclusion and Discussion

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 32.95% 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 about 28% below pre-pandemic levels. 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.

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 these changes in the future of work.

Trends in office occupancy have prompted discussion on the merits of conversion of office, either from A-/B/C to A+ office or to alternative use such as multi-family. The former conversion could make sense in light of the flight to quality and the likely dearth of new office construction for years to come. The latter conversion makes sense in light of the lack of affordable housing in large cities, but often runs into issues relating to the physical feasibility, zoning restrictions, and financial cost. 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.

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.[19] 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.

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A Asset Pricing Model to Infer Expected Returns

We consider a simple asset pricing model that can help explain office valuations and how WFH has impacted them. Conceptually, WFH has affected current building cash flow levels, expectations of future cash flow growth rates, and discount rates. The previous sections discussed the impact on current cash flows and on expected future rent growth. In this section, we develop a simple model to help understand how expected returns (risk premia) were affected during this period.

A.1 Model for Expected Returns

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

$$x_t \equiv \mathbb{E}_t[r^o_{t+1}] = r^f_t + \beta^m_t \lambda^m + \beta^b_t \lambda^b + \beta^{wfh}_t \lambda^{wfh} \tag{8}$$

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

A.2 Constructing a WFH Risk Factor

We form a portfolio (Working from Home Index) that goes long stocks that benefit from remote work and short stocks that suffer from the move to working-from-home. Our benchmark WFH factor goes long stocks in the technology sector, health care sector, and pharmaceutical companies developing vaccine candidates and short stocks in the transportation sector, entertainment sector, and hotel sector. The WFH index composition can be found in table 5. 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 Working from Home 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 weight $w_{i,l,r}$ and each stock j in the short leg is assigned weight $w_{j,s,r}$

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

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

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

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:

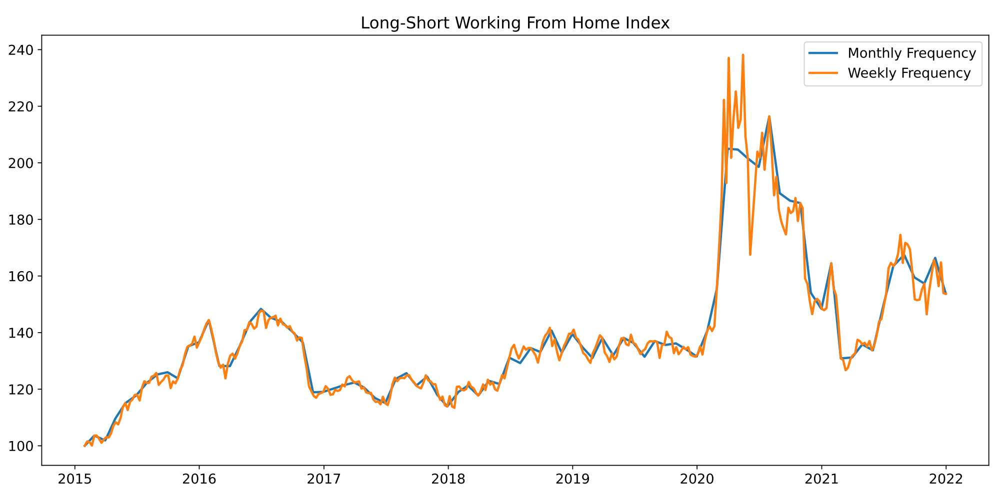
$$R_t = R_{l,t} - R_{s,t}$$

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 yet, such as Zoom. Several perturbations on the WFH index construction deliver similar results. Figure 15 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 15: Working From Home Risk Factor



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

Table 5: 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

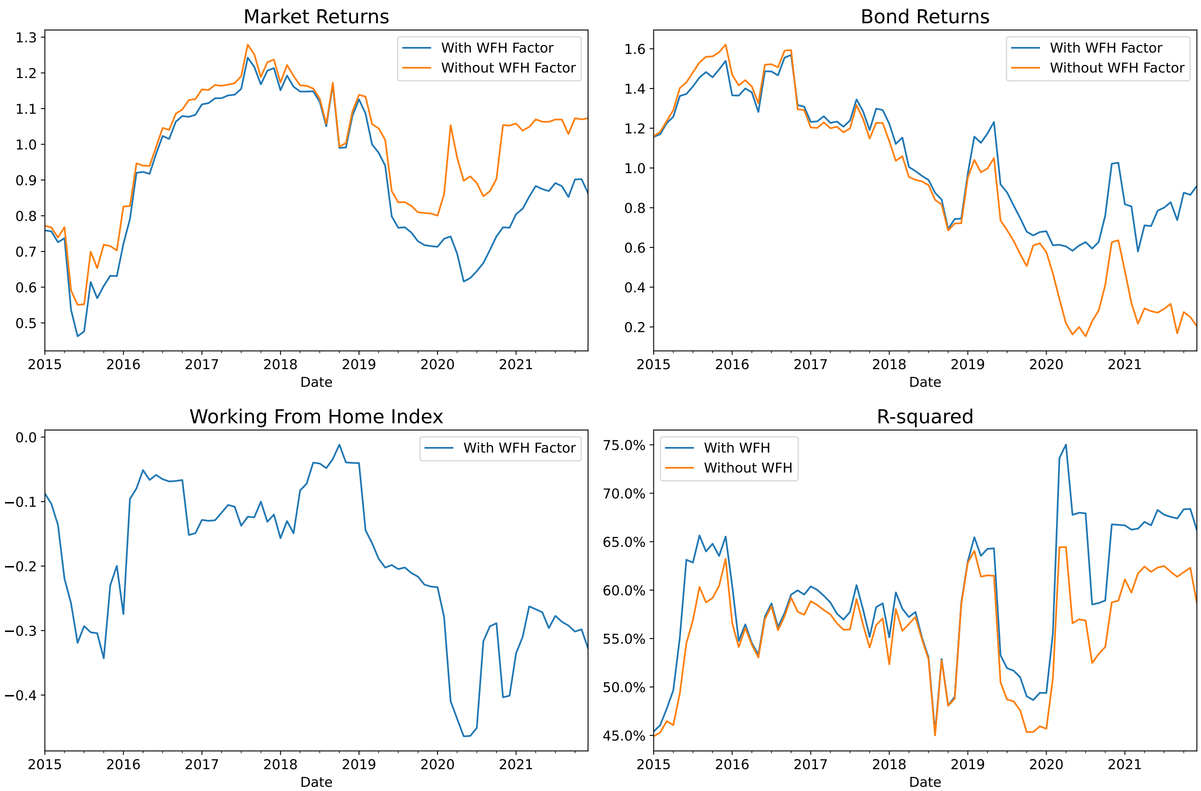
To show that WFH risk emerged in full force during the pandemic, we estimate time-varying betas from 36-month rolling-window regressions for monthly office REIT excess returns:

$$r^o_{t+1} - r^f_t = \alpha + \beta^m_t (r^m_{t+1} - r^f_t) + \beta^b_t (r^b_{t+1} - r^f_t) + \beta^{wfh}_t r^{wfh}_{t+1} + e_{t+1} \quad (9)$$

Figure 16 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 until 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 up at -0.3 in December 2021. The bottom-right panel shows that the R^2 improves during the pandemic thanks to the inclusion of the WFH factor.

Figure 16: 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 REIT returns. We use a two-stage Fama-MacBeth procedure. In the first time-series stage, we estimate 36-month rolling-window regressions of each REIT's return on the three factor returns; i.e., we estimate equation (9) 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 (January 2015-January 2020) 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).[20]

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 pandemic flared up. Conversely, negative returns to WFH, such as Nov 8, 2020 when the vaccine discovery news first broke, are good states of the world.

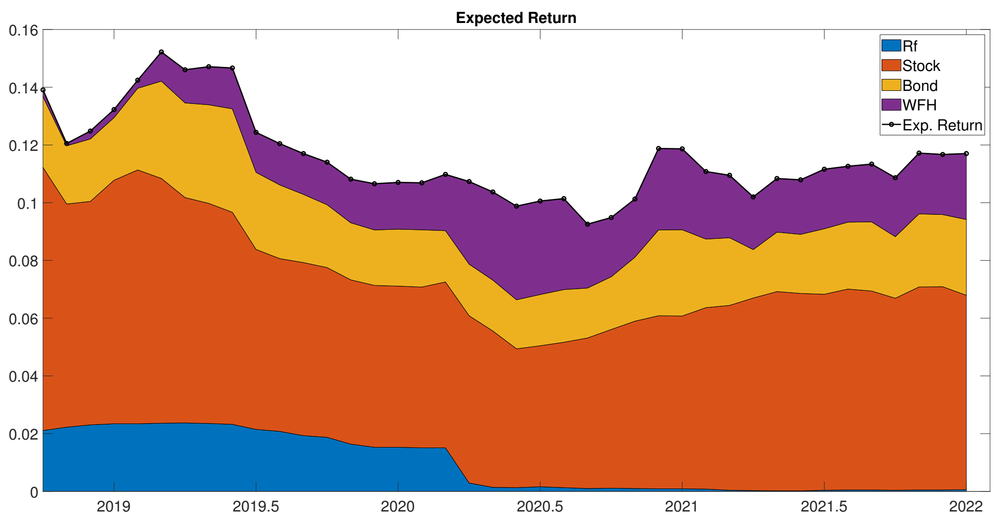
A.5 Expected Returns

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 $\lambda^{wfh} = -7.0\%$, estimated above. We combine the three time-varying betas from Figure 16 with the market price of risk estimates to form the expected return on office REITS as per equation (8). Figure 17 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 (January 2015-December 2019) to 10.79% during the pandemic (January 2020-December 2021), a decline of 207 basis points. In December 2021, the expected return climbs back up to 11.7%.

[20] Repeating 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 17: Expected Return of Office REITs During Covid



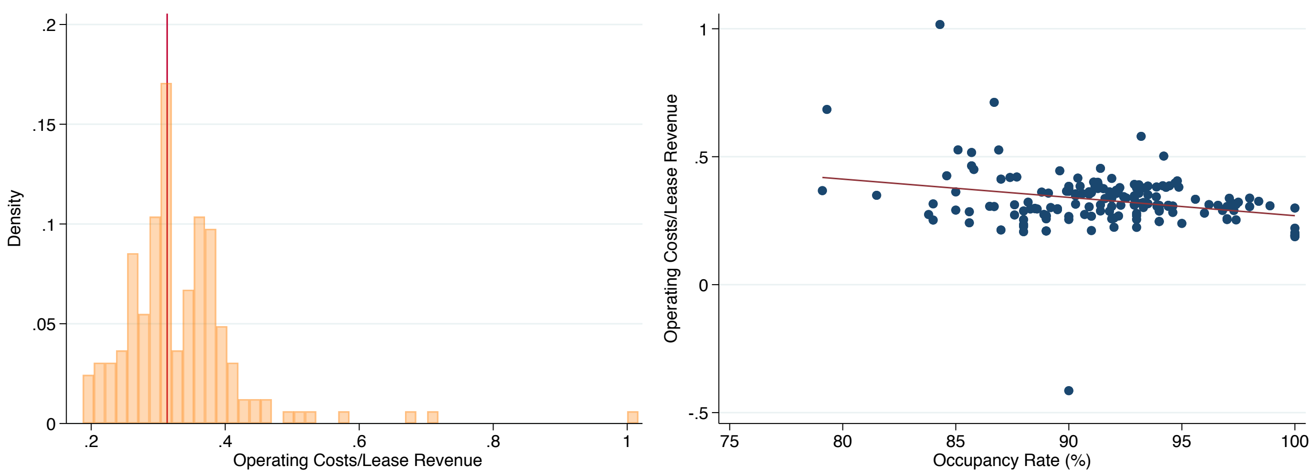
B REIT Financial Data

B.1 Evidence from REIT Financials

Having observed granular lease revenue from CompStak data, we now turn to office REIT financials to measure the pass-through of lower rent revenues into lower net cash flows.

Figure 18 plots the density of operating costs divided by lease revenue in the left panel, and against the occupancy rates in the right panel, pooling all office REITs and years. The full list of office REITs is in Appendix Table 7. The median ratio of operating costs to lease revenue ratio is 0.313, with substantial dispersion around the median. The right panel shows that a higher occupancy rate is associated with a lower operating costs to lease revenue ratio. This is indicative of the fact that some operating expenses are fixed in nature, and can be amortized over a larger tenant base as occupancy rises.

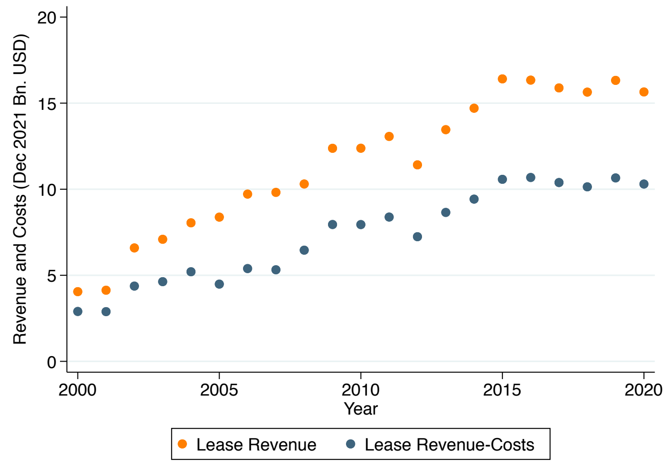
Figure 18: Office REITs Property Operating Costs/Lease Revenue



Next, we study the pass-through of lease revenues to cash flows. In the time-series, Figure 19 plots lease revenue and lease revenue minus operating costs over time, aggregated across all office REITs. The numbers are deflated by CPI and expressed in 2021 USD. The figure suggest that operating costs are roughly proportional to lease revenues.

Table 6 shows the pass-through from lease revenue of office REITs to different measures

Figure 19: Lease Revenue and Operating Costs Over Time



of net cash flows, considering years from 2000–2020. Column (2) indicates that an additional \$1 in lease revenue per sqft translates into \$0.61 of lease revenue minus costs. When we consider REIT and year fixed effects in Column (4), we obtain a pass-through of \$0.54.

Table 6: Pass-Through From Lease Revenue to Net Cash Flows

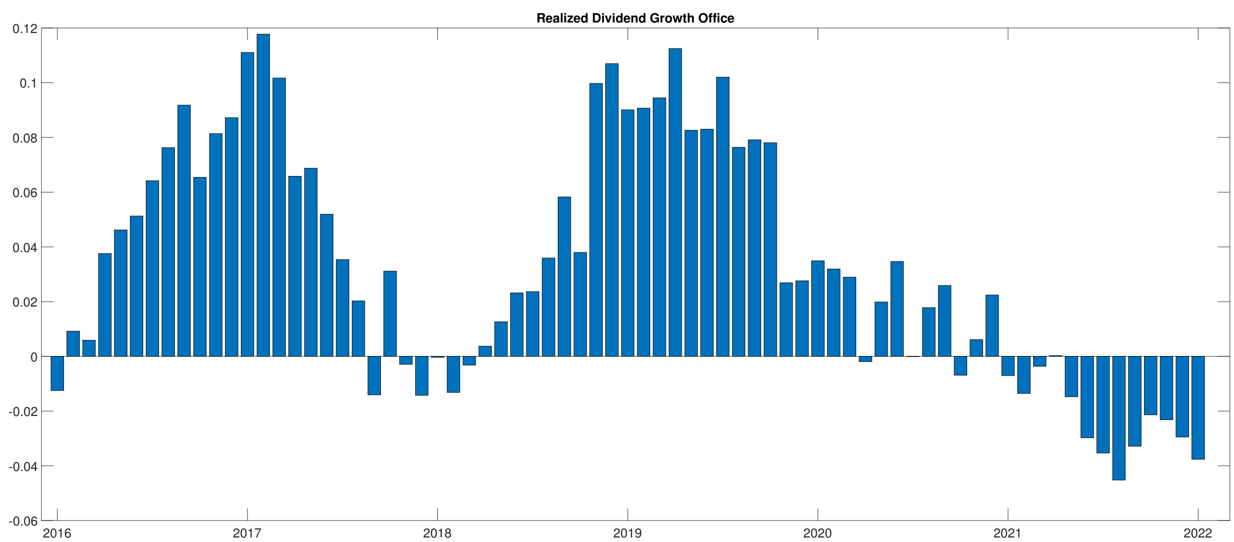
	(1) FFO /sqft	(2) LR-C /sqft	(3) FFO /sqft	(4) LR-C /sqft
Lease Revenue /sqft	0.328***	0.612***	0.390***	0.538***
	(9.75)	(36.47)	(4.48)	(23.85)
Constant	3.510***	1.483***	1.483	3.714***
	(2.95)	(2.64)	(0.52)	(5.40)
REIT FE			✓	✓
Year FE			✓	✓
Observations	148	171	148	171
R squared	0.394	0.887	0.659	0.979

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

Assuming that REIT landlords have representative pass-through from lease revenue to net cash flow, the \$4 billion reduction in lease revenues observed for the Compstak sample during the pandemic translates into a \$2.16 billion reduction in net cash flow. The proportionality of operating expenditures and lease revenue suggests that a 7.0% decline in lease revenue generates an equal 7.0% decline in net cash flow.

Figure 20 shows the realized dividend growth rate, extracted from the NAREIT cum- and ex-dividend returns on their REIT office index. It plots the year-over-year log change in the realized dividend paid out in the current and past 11 months. Dividend growth was 3.5% in December 2019, i.e., the total dividends paid during 2019 were 3.5% points higher than total dividends paid during 2018. In December 2020, dividend growth had fallen to -0.7%. That is, full-year 2020 dividends were 0.7% lower than full-year 2019 dividends. In December 2021, FY dividends were 3.8% points lower than a year before. The 4.5% point cumulative drop in the level of dividends over the course of the pandemic is similar to the 5.5% decline in lease revenues for A+ office measured in the Compstak data (Figure 1).

Figure 20: Realized Dividend Growth of Office REITs During Covid



B.2 Description of REIT Financial Data

We collect annual financial data of REITs from 10-K financial statements filed to the SEC. We notice several discrepancies in the same year statistic filed by the REITs across 10-Ks. Further, the reporting patterns are different across REITs, and over time for the same REIT. Below, we describe the methodology we undertake to make the data consistent.

We collect the statistic for a particular REIT-year from the 10-K filed by the REIT in that particular year. For instance, CXP reports total revenue for 2008 as different numbers in the 10-Ks filed for financial years 2008 and 2009, and no amendment is filed for such a discrepancy. We take the 2008 total revenue from the 10-K for financial year 2008. A similar practice is followed for all statistics and REITs.

Total lease revenue consists of rental income and tenant reimbursements. Often times, rental income is referred to as base rent or rent income. Other income is not considered in the calculations for total lease revenue. *Total revenue* includes other income.

Funds from Operations or cash available for distribution is attributable to common stockholders and non-controlling interests. *Net income* adjusts for other income (expense) such as interest income (expense), IPO litigation expense, gain (loss) from derivative financial instruments. It also considers operating expenses include property operating expenses, gound rent expenses, real estate taxes, depreciation and amortization etc. *Operating property expenses* only includes expenses associated with renting and maintaining the properties, such as repair and maintenance costs, payroll costs, utility costs and professional fees.

We also obtain *net rentable square feet* and *occupancy rate* from the REIT 10-K reports. In case, we have both occupancy rates and leasing rates, we consider occupancy rates, as that corresponds to the revenue currently being generated by the properties. Note that % Occupied $\leq$ % Leased. In most cases,

$$\text{Leased SqFt} = \text{Net Rentable SqFt} \times \text{Occupancy Rate}$$

Many office REITs hold properties across sectors: office, retail, industrial etc. We consider rentable area and occupancy rates of the office sector properties, if available separately by sector. Boston Properties, Inc. (BXP) includes office sector plus office/technical sector properties. We also focus on properties in the U.S. by geography. If we don't have these statistics by geography and sector, we use the REIT level statistics. Additionally, we only consider the properties in the operating portfolio of the REIT, which excludes the redevelopment and construction properties. This is commensurate with considering the properties generating revenue in the corresponding financial year.

Table 7: 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

C Model Derivation

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

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

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

C.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:

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

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,

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

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

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

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

R_t^O is the average net effective rent per sqft on existing leases, and R_{t+1}^m is the market net effective rent per sqft 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,

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

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

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

Let's define the state variable $\hat{R}_t^O$ as,

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

We want to find the law of motion for the scaled state variable $\hat{R}^O_{t+1}$:

$$
\begin{aligned}
\hat{R}^O_{t+1} &= \frac{R^O_{t+1}}{R^m_{t+1}} \\
\hat{R}^O_{t+1} &= \frac{(1-\chi)R^O_t + \chi R^m_{t+1}}{R^m_{t+1}} \\
\hat{R}^O_{t+1} &= \frac{(1-\chi)R^O_t}{R^m_{t+1}} + \chi \\
\hat{R}^O_{t+1} &= \frac{(1-\chi)\hat{R}^O_t R^m_t}{R^m_{t+1}} + \chi \\
\hat{R}^O_{t+1} &= \frac{(1-\chi)\hat{R}^O_t}{1+\epsilon_{t+1}(z')} + \chi
\end{aligned}
$$

Let's define scaled revenues as

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

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

$$
\begin{aligned}
Rev_{t+1}(\hat{Q}^O_t, \hat{R}^O_t, z') &= \hat{Q}^O_t \bar{Q}_t (1-\chi)\hat{R}^O_t R^m_t + \left[\hat{Q}^O_t \bar{Q}_t \chi s^O_{t+1}(z') + (\bar{Q}_t - \hat{Q}^O_t \bar{Q}_t) s^V_{t+1}(z')\right] R^m_t (1+\epsilon_{t+1}(z')) \\
Rev_{t+1}(\hat{Q}^O_t, \hat{R}^O_t, z') &= \bar{Q}_t R^m_t \Big[\hat{Q}^O_t (1-\chi)\hat{R}^O_t + \left[\hat{Q}^O_t \chi s^O_{t+1}(z') + (1-\hat{Q}^O_t) s^V_{t+1}(z')\right](1+\epsilon_{t+1}(z'))\Big]
\end{aligned}
$$

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

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

The Expected PDV of Revenues is written as

$$
V^R_t = E_t\Big[\sum_{j=1}^{\infty} M_{t,t+j} Rev_{t+j}\Big]
$$

The scaled version is:

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

which solves the following Bellman equation:

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

Finally, we get V_t^R by

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

C.2 Costs

The building costs are written as:

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

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

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

Defining scaled costs as:

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

Therefore, we have:

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

where

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

The Expected PDV of Costs is written as:

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

The scaled version is:

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

which solves the Bellman equation

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

Finally, we get V_t^C by

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

C.3 Closed-form solutions

First, we define matrix notations for parameters:

$$\mathbb{1}_{4x1} = \Big[1, 1, 1, 1\Big]'$$

$$E_{4x4} = \Big[\epsilon_{4x1},\, \epsilon_{4x1},\, \epsilon_{4x1},\, \epsilon_{4x1}\Big]'$$

$$H_{4x4} = \Big[\eta_{4x1},\, \eta_{4x1},\, \eta_{4x1},\, \eta_{4x1}\Big]'$$

$$S_{4x4}^O = \Big[s_{4x1}^O,\, s_{4x1}^O,\, s_{4x1}^O,\, s_{4x1}^O\Big]'$$

$$S^V_{4x4} = \left[s^V_{4x1}, \, s^V_{4x1}, \, s^V_{4x1}, \, s^V_{4x1} \right]'$$

C.3.1 Cost Valuation

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

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

where

$$a(z') = c^{fix}_{t+1}(z') + (1 + \epsilon(z')) \cdot s^V_{t+1}(z') LC^N_{t+1}(z'),$$

$$b(z') = c^{var}_{t+1}(z') + \big(1 + \epsilon(z')\big) \cdot \left[\chi s^O_{t+1}(z') LC^R_{t+1}(z') - s^V_{t+1}(z') LC^N_{t+1}(z') \right]$$

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

$$\begin{aligned}
\frac{\partial \hat{V}^C_t}{\partial \hat{Q}^O_t}(\hat{Q}^O_t, z) &= \sum_{z'} \pi(z'|z) M(z'|z) \left\{ b(z') + (1 + \eta(z'))(1 + \epsilon(z')) \frac{\partial \hat{V}^C_{t+1}}{\partial \hat{Q}^O_t}(\hat{Q}^O_{t+1}, z') \right\} \\
&= \sum_{z'} \pi(z'|z) M(z'|z) \left\{ b(z') + (1 + \epsilon(z'))(1 - \chi + \chi s^O_{t+1}(z') - s^V_{t+1}(z')) \frac{\partial \hat{V}^C_{t+1}}{\partial \hat{Q}^O_{t+1}}(\hat{Q}^O_{t+1}, z') \right\}
\end{aligned}$$

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

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

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

$$\hat{V}^C_{4x1} = a^C_{4x1}(z) + b^C_{4x1}(z) \cdot \hat{Q}^O_t$$

where[21]

$$b^C_{4x1}(z_{4x1}) = \left(I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ \left(1 - \chi + \chi S^O_{4x4} - S^V_{4x4}\right)\right)^{-1}_{4x4} \cdot$$
$$(\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \left(c^{var}_{4x1} + (1 + \epsilon_{4x1}) \circ \left(\chi s^O_{4x1} \circ LC^R_{4x1} - s^V_{4x1} \circ LC^N_{4x1}\right)\right)_{4x1}$$

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:

$$a^C_{4x1}(z_{4x1}) = (I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ (1 + H_{4x4}))^{-1}_{4x4} \cdot$$
$$(\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \left(c^{fix}_{4x1} + (1 + \epsilon_{4x1}) \circ \left(s^V_{4x1} \circ LC^N_{4x1} + b^C_{4x1} \circ s^V_{4x1}\right)\right)_{4x1}$$

C.3.2 Revenue Valuation

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

$$\frac{\partial^2 \hat{V}^R_t}{\partial \hat{Q}^O_t \partial \hat{R}^O_t} = d^R(z) \tag{10}$$

where

$$d^R_{4x1}(z_{4x1}) = \left(I - \pi_{4x4} \circ M_{4x4} \circ (1 - \chi) \circ \left(1 - \chi + \chi S^O_{4x4} - S^V_{4x4}\right)\right)^{-1}_{4x4} \cdot$$
$$(\pi_{4x4} \circ M_{4x4})_{4x4} \cdot (1 - \chi \cdot \mathbb{1}_{4x1})_{4x1}$$

Next, we integrate equation (10) by $\hat{Q}^O_t$:

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

[21]We 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 $\hat{R}_t^O$:

$$\frac{\partial \widehat{Rev}_{t+1}}{\partial \hat{R}_t^O} = (1-\chi) \cdot \hat{Q}_t^O \tag{11}$$

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:

$$\begin{aligned} c^R_{4x1}(z_{4x1}) = &\left(I - \pi_{4x4} \circ M_{4x4} \circ (1 + H_{4x4}) \circ (1-\chi)\right)^{-1}_{4x4} \cdot \\ &(\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \Big((1-\chi) \circ s^V_{4x1} \circ d^R_{4x1}\Big)_{4x1} \end{aligned}$$

Following the same logic, by taking integral w.r.t. $\hat{R}_t^O$ in equation (10) and check the independence of instantaneous reward:

$$\frac{\partial \hat{V}_t^R}{\partial \hat{Q}_t^O} = b^R(z) + d^R(z) \cdot \hat{R}_t^O \tag{12}$$

where

$$\begin{aligned} b^R_{4x1}(z_{4x1}) = &\Big(I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ \Big(1 - \chi + \chi S^O_{4x4} - S^V_{4x4}\Big)\Big)^{-1}_{4x4} \cdot \\ &(\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \Big((1+\epsilon_{4x1}) \circ \Big((\chi s^O_{4x1} - s^V_{4x1}) \circ (1 + \chi d^R_{4x1}) + (1-\chi)\chi d^R_{4x1}\Big)\Big)_{4x1} \end{aligned}$$

Then, we integrate equation (11) w.r.t. $\hat{R}_t^O$ and equation (12) 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:

$$a^R_{4x1}(z_{4x1}) = (I - \pi_{4x4} \circ M_{4x4} \circ (1 + E_{4x4}) \circ (1 + H_{4x4}))^{-1}_{4x4} \cdot$$
$$(\pi_{4x4} \circ M_{4x4})_{4x4} \cdot \Big((1 + \epsilon_{4x1}) \circ \Big(s^V_{4x1} \circ (1 + b^R_{4x1} + \chi d^R_{4x1}) + \chi(1 + \eta_{4x1}) \circ c^R_{4x1}\Big)\Big)_{4x1}$$

C.4 Strip Decomposition

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

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

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

The revenue strips can be priced recursively:

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

starting from

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

Scaling by potential gross revenue

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

starting from

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

since

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

There is a closed-form expression for each $\widehat{V}_t^{R,(j)}$ 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 $\widehat{V}_t^R$.

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

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 $b^{C,(j)}(z)$.

D Results for NYC A+ Market

Appendix Table 8 shows the model solution for the A+ calibration. The model delivers a lower cap rate of 3.5% for A+ NYC office, largely due to a higher expected cash flow growth rate of 2.1%. Class A+ has lower vacancy levels than the market as a whole, on average as well as in the WFH states. Appendix Figure 21 shows the valuation ratio $\widehat{V}$ in each state as a function of occupancy and rent state variables.

Table 8: Model Solution for NYC A+

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.035	0.034	0.041	0.034	0.040
Office $\mathbb{E}[Ret] - 1$	0.057	0.044	0.125	0.042	0.119
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.042	0.035	0.078	0.034	0.072
$\mathbb{E}\left[g_t\right]$	0.021	0.015	0.067	0.004	0.045
Vacancy rate $= 1 - \widehat{Q}^O$	0.117	0.102	0.130	0.140	0.163
$\widehat{\text{Rev}}$	0.806	0.811	0.844	0.776	0.799
$\widehat{\text{Cost}}$	0.422	0.427	0.421	0.414	0.408
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.384	0.383	0.423	0.362	0.391
$\widehat{V}^R$	21.078	21.802	19.373	20.671	18.489
$\widehat{V}^C$	10.030	10.400	8.991	9.920	8.685
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	11.048	11.402	10.381	10.751	9.804

Figure 21: $\hat{V}$ for NYC A+ Market by States