Work From Home and the Office Real Estate Apocalypse*

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Abstract

We show remote work led to large drops in lease revenues, occupancy, lease renewal rates, and market rents in the commercial office sector. We revalue New York City office buildings taking into account both the cash flow and discount rate implications of these shocks, and find a 44% decline in long run value. For the U.S., we find a $506.3 billion value destruction. Higher quality buildings were buffered against these trends due to a flight to quality, while lower quality office is at risk of becoming a stranded asset. These valuation changes have repercussions for local public finances and financial stability.

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1 Introduction

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 to 10% of pre-pandemic levels at the end of March 2020, and has remained depressed ever since, creeping back to 50% by May of 2023. In the intervening period, work-from-home (WFH) practices have become more established, with many firms announcing permanent remote or hybrid work arrangements and shrinking physical footprints. These shifts in current and projected future office demand have led to concerns that commercial office buildings may become a stranded asset in the wake of disruptions resulting from remote work. Because office assets are often financed with debt which resides on banks' balance sheets and in Commercial Mortgage-Backed Security (CMBS) portfolios, large declines in value would have consequences for institutional investors and for financial stability.[1] The spatial concentration of office assets in urban central business districts also poses fiscal challenges for local governments, which rely heavily on property taxes levied on commercial real estate to provide public goods and services. A decline in office and adjacent retail real estate valuations may activate a fiscal "urban doom loop" that lowers the quality of life for urban residents and worsens the business climate.

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

The value of office reflects the expected present discounted value of its cash flows. We begin by analyzing the shock to cash flows between the end of 2019 and the end of 2022. Using a unique data set from CompStak, we study lease-level data for 105 office markets throughout the United States over the period from January 2000 until December 2022. We

[1]Investable commercial real estate assets were worth about $4.7 trillion at the end of 2019, of which office represents the largest component. They make up an important part of the portfolio allocation to "real assets" of a growing number of institutional investors (Goetzmann, Spaenjers and Van Nieuwerburgh, 2021). Banks have about $2.4 trillion in commercial real estate loans on their balance sheets as of June 2022 according to Call Report data. They account for 61% of CRE debt.

document a 18.51% decrease in lease revenue in real terms between December 2019 and December 2022. Two-thirds of this decline reflects decreases in the quantity of in-force leases. The remainder is accounted for by declines in real rents on in-force leases. The quantity of newly-signed leases in our data set falls from 285.38 million square feet per year just before the pandemic to 62.39 million square feet in December 2022. Rents on newly-signed leases fell by 9.16% in real terms between December 2019 and December 2020 before reversing to pre-pandemic levels by the end of 2021, with meaningful heterogeneity across cities. Because a large fraction of leases in-force at the end of 2019 did not come up for renewal in 2020, 2021, or 2022 (63.95% in the U.S., 73.52% in New York), and vacancy rates are already at 30-year highs in several major markets (22.2% in New York in 2023.Q1), rents may not have bottomed out yet.

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

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

Because most of the office stock is not publicly-traded (and this segment is also disproportionate high-quality) and sales of privately-held office properties slowed down dramatically during the pandemic, it is not possible to rely on transaction data to infer the changes that remote work wrought onto office values. To address this challenge, a central contribution of our paper is to build a novel asset pricing model to infer the changing values.

Office values reflect expectations of future cash flows and discount rates. The model is a bottom-up valuation tool, adapted to the details of commercial real estate assets. A property is a portfolio of long-term leases. The model features long lease duration, leasing risk, market rent risk, and supply growth risk. We aggregate lease revenues to the property level and subtract costs to arrive at net operating income (NOI). We discount NOI with the stochastic discount factor (SDF) to obtain the property's value. The model aggregates so we can compute the value of (a segment of) the office market as a portfolio of office properties. There are two sources of aggregate risk: standard business cycle risk and aggregate uncertainty regarding the state of remote work, with stochastic transitions between a no-WFH and a WFH state. Rent growth, supply growth, lease renewals, new lease signings, and operating costs vary across aggregate states.

Our main calibration exercise focuses on the New York City (NYC) office market. The model matches market rent, supply, and vacancy dynamics in the data. This includes the sharp increase in office vacancy rates between the end of 2019 and 2022. The model's SDF is chosen to match the observed risk-free interest rate, the equity risk premium in the stock market (and its fluctuation across recessions and expansions), and the returns on a new WFH risk factor, which we create. The WFH risk factor goes long stocks that benefit from remote work (i.e., Zoom) and goes short stocks which are hurt by it (i.e., airlines).

A key parameter that affects the change in office valuations due to WFH is the persistence of WFH practices. We back out this parameter from the (unlevered) stock return on NYC-centric office REITs observed between December 2019 and December 2020. Since REITs predominantly invest in A+ office product, we do a separate calibration to the A+ segment of the NYC office market. The model matches the 2020 (unlevered) office return for an annual persistence parameter of 0.94, indicating that office investors believe remote-work practices to be long-lasting. We show sensitivity of our conclusions to the value of this persistence parameter.

With this parameter in hand, we return to the full NYC office market calibration. We obtain a 46.1% reduction in the value of the entire NYC office stock between December 2019 and December 2020. Simulating the model forward for ten years, we characterize the mean value of the office stock and—just as importantly—the uncertainty around this valuation, which depends on the sequence of shocks that hits the economy. Along the average path, office occupancy stabilizes and the economy returns to the no-WFH state with some probability. These mean-reversion forces push office valuations towards an average office value in 2029 that is about 43.9% below 2019 values. Along paths where the economy remains in the WFH state, office values in 2029 are 51.6% below their 2019 values. Hence, there is substantial uncertainty about future office values, *WFH risk*, that our approach quantifies.

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

What do these numbers imply for the aggregate value of the office stock? We calculate a reduction in value of the office stock between the end of 2019 and 2022 of $69.6 billion for NYC, $32.7 billion for San Francisco, and $5.1 billion for Charlotte. For the remaining office markets, we combine market-specific lease revenue declines with valuation ratio changes for NYC to compute the value decline. Nationwide, we find a $506.3 billion decline in office values in the three-year period.

The key takeaway from our analysis is that remote work is shaping up to massively disrupt the value of commercial office real estate in the short and medium term. This conclusion is consistent with our finding that firms appear to demand substantially less office space when they adopt hybrid and remote work practices, and that such practices appear to be persistent. In the long run, firms may discover that the productivity or innovation impact from remote work is worse or better than expected, remote-work technologies may improve further, and cities may repurpose existing office assets to alternative use. These changes are likely to play out over decades and are beyond the horizon of our analysis. That said, our model calibration features a reduction in office supply in the WFH state, capturing reduced construction activity and adaptive reuse of office assets in the WFH state.

Related Literature Our work relates to four literatures. We relate closely to the rapidly growing literature on the measurement of remote work and its impact on real estate, surveyed in Van Nieuwerburgh (2023). Bick, Blandin and Mertens (2023); Bartik, Cullen, Glaeser, Luca and Stanton (2020); Barrero, Bloom and Davis (2021); Aksoy, Barrero, Bloom, Davis, Dolls and Zárate (2022); Brynjolfsson, Horton, Makridis, Mas, Ozimek, Rock and TuYe (2023) measure the prevalence of WFH, including with new survey instruments, tie the bulk of its growth to new work arrangements, and argue that WFH is expected to last. 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. Hoesli and Malle (2022) analyze the effect of the pandemic on commercial real estate in Europe and Cohen, Friedt and Lautier (2020) in New York City. Gupta, Mittal, Peeters and Van Nieuwerburgh (2022); Brueckner, Kahn and Lin (2021); Ramani and Bloom (2021); Mondragon and Wieland (2022) study the impact of work from home on residential real estate prices and rents.

An important urban economics branch of this literature explores the effects of remote work in quantitative general equilibrium models of labor and real estate markets (Delventhal, Kwon and Parkhomenko, 2021; Davis, Ghent and Gregory, 2021; Li and Su, 2021; Gokan, Kichko, Matheson and Thisse, 2022; Monte, Porcher and Rossi-Hansberg, 2023). These models are well-suited for thinking about long-run implications of remote work on city structure, including how office space could be repurposed for alternative purposes. This paper uses micro data on office leases to document changes in commercial real estate markets with the rise in remote work, and uses these data as inputs in a new asset pricing model. The finance perspective, which places WFH risk at the core, focuses on risk and transition dynamics and is a useful complement to the urban economics perspective. An important challenge for future work is to integrate these two approaches.

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

Finally, an interesting strain of finance research has focused on identifying disruptive technological shocks to asset prices. An important topic in this literature has been that of stranded assets: whether innovation or climate change have the potential to transform existing assets into liabilities, with consequences for the creative destruction of economic activity (Gârleanu, Kogan and Panageas, 2012; Kogan and Papanikolaou, 2014, 2019; Barnett, Brock and Hansen, 2020; Pástor, Stambaugh and Taylor, 2022; Eisfeldt, Schubert and Zhang, 2023). We contribute to this literature by documenting a novel disruptive shock in the form of remote work, proposing a WFH risk factor, and highlighting exposure of urban commercial real estate assets to the WFH factor.

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, and identifying remote work as the key driver. Section 3 estimates the valuation of office buildings in the context of a structural model, and Section 4 highlights the implications for office valuation. Section 5 concludes. Appendix A contains additional empirical results. Appendix B details the construction of the WFH risk factor. Appendix C provides model derivations. Appendix D details the calibration algorithm. Appendix E reports model results for high-quality offices. Appendix F contains the calibration details for San Francisco and Charlotte. Appendix G reports additional results from the model.

2 The Office Market During the Pandemic

2.1 Data

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

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

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

In public markets, we obtain monthly returns for office REITS included in the National Association of Real Estate Investment Trust (NAREIT) office index for the period 2019–2022.

To measure remote working conditions at the firm level, we use information from Scoop, which provides a Flex Index containing information on the full time, hybrid, and fully remote working practices of over 3,000 firms. This allows us to measure remote working plans by office tenants and connect them to their leasing decisions.[2]

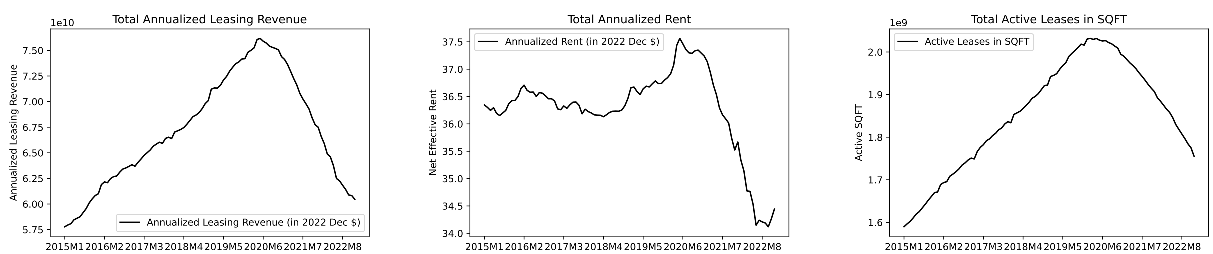
[2]We also explore a job postings measure drawn from Ladders, an online job search service site. The platform

2.2 Shock to Leasing Revenue

We begin by highlighting the first component of the valuation shock: the reduction in current leasing revenue. The total value of annualized leasing revenue on *in-force* office leases was \$74.19 billion prior to the pandemic in December 2019 (all numbers expressed in December 2022 dollars). Total leasing revenue experienced a 18.51% decline nationwide, falling to \$60.46 billion in December 2022. This decline is substantial in light of the long-term nature of office leases. It indicates substantial shifts in leasing activity among those tenants in a position to make a choice about their office space needs. Figure 1, Panel A, plots the time series of total leasing revenue.

Figure 1: Revenues on In-Force Leases

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



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

This decline can be separated into the shocks to rents and to quantities. Throughout the paper, we use the concept of net effective rent (NER).[3] Annualized NER on in-force leases fell in real terms throughout the pandemic. Most leases in force in 2020–22 were signed before 2020 and have built-in nominal rent escalation clauses. However, the scheduled rent increases were not large enough to keep pace with inflation, leading to a real NER drop on in-force leases of 6.40% (Panel B of Figure 1). Below, we also show that NERs on *new* leases signed in the first year of the pandemic fell substantially below pre-Covid rent levels.

focuses on job positions paying in excess of \$100,000 a year, and so has high coverage of many remote working positions for knowledge workers. We measure the fraction of job postings which mention fully remote terms at the firm level.

[3]The NER augments the standard contract rent schedule—a rent for each month over the course of the lease—with additional provisions including rent concessions (free rent) as well as tenant improvements (work paid for by the landlord). The resulting NER reflects the average rent earned by the landlord, and is the most relevant object in understanding changing market rent dynamics.

The quantity of in-force leases (in square feet) fell substantially during the pandemic. The decline is 12.93% between December 2019 and December 2022 (Panel C). This decline reflects (i) difficulties in filling vacant space with new tenants, (ii) lack of lease renewals by existing tenants whose lease is up for renewal, and (iii) renewals for less space than the prior lease. This suggests that understanding the quantity dimension is of utmost importance when it comes to understanding shocks to pandemic cash flows.

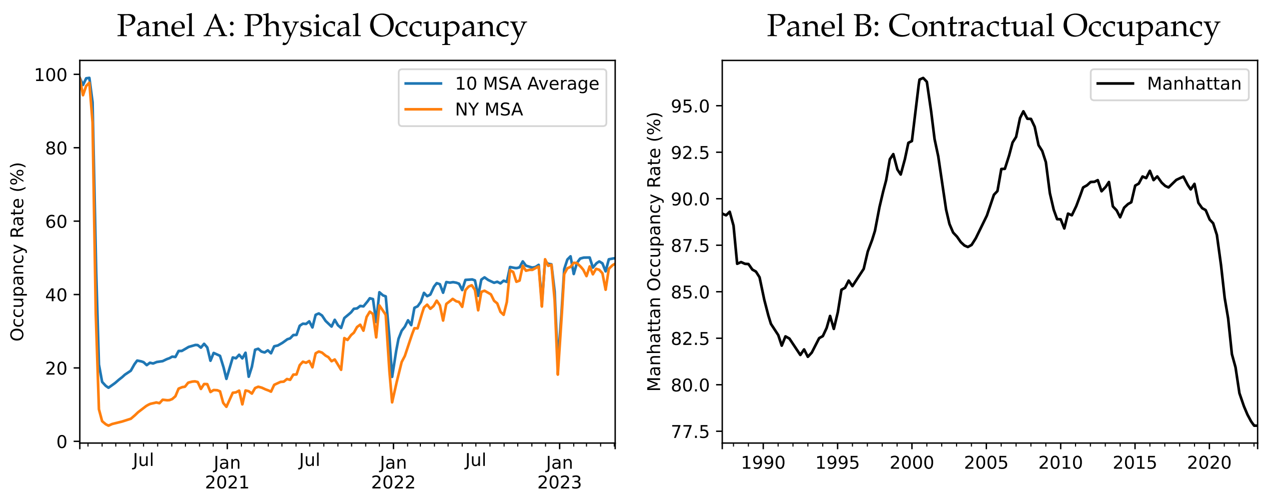
2.3 Physical Occupancy, Contractual Occupancy, and Lease Expiration

In Figure 2 (Panel A) we highlight the key shift which is the focus of our paper: the sudden drop in physical office presence for white-collar workers. Physical office occupancy is measured from turnstile data provided by Kastle.[4] Over the course of the pandemic, about 70% of college-educated workers did some or all of their work from home. In the initial wave of the pandemic, physical office occupancy rates fell to just 20% among the top-10 largest office markets (10% in NYC). Average occupancy recovered to about 30% (20%) by the end of 2020. It saw several more dips as the pandemic intensified in early 2021. The recovery continued in the second half of 2021 to about 40% (35%), before falling sharply due to the rise of the Omicron variant at the end of 2021. The latest data as of early May 2023 show a 49.9% occupancy rate among the largest 10 office markets (48.4% in NYC). With over three years of remote work experience, many employers and employees have formed new habits and expectations. Employees have come to like remote work and report being more productive. Employers have revised upward their own longer-run expectations on average employee days worked from home (Barrero et al., 2021; Aksoy et al., 2022), and have begun to adjust their demand for office space, as shown in more detail below.

These large drops in physical occupancy did not translate into large immediate drops in commercial office cash flows, as shown above. The reason for the gradual reaction is the staggered nature of commercial leases, highlighted in Figure 3. Because most commercial

[4] The Kastle data cover more than 2,600 buildings in 138 cities. Other data sources, such as subway usage or the Partnership for New York survey, accord well with the Kastle data.

Figure 2: Office Occupancy

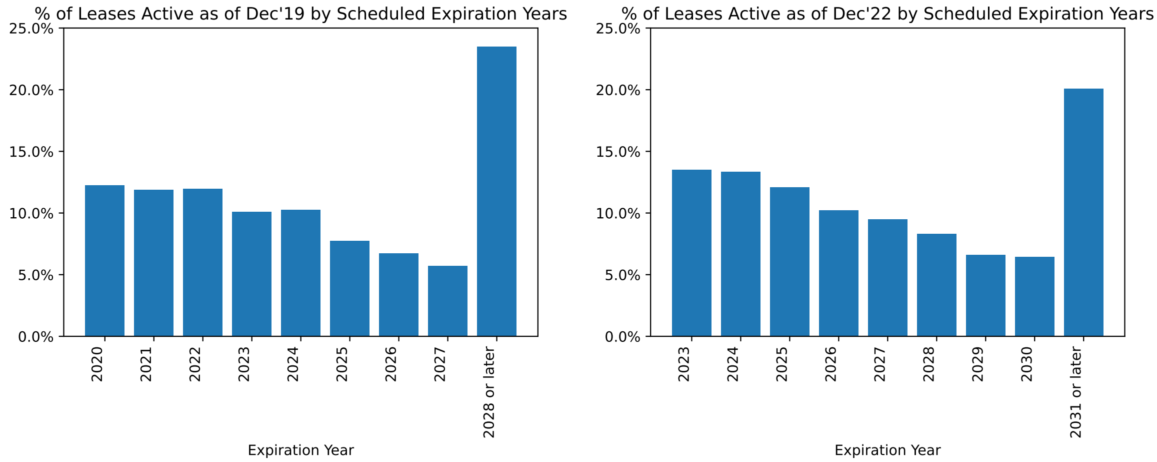


Notes: The figure shows office physical (Panel A) and contractual (Panel B) occupancy over time. Physical occupancy is sourced from Kastle. Contractual occupancy is sourced from Cushman & Wakefield.

leases are long-term, and not up for immediate renewal, only a fraction of office tenants have had to make active choices about their future office demand so far. Among all in-force leases as of the end of December 2019, only 36.05% by square feet came up for renewal in 2020, 2021, and 2022 combined. Nearly all of the tenants not up for renewal have continued to make rent payments, despite their lack of physical occupancy. When more leases come up for renewal in the future, the office demand of tenants who have made limited use of office space during the pandemic remains highly uncertain and is a crucial determinant of office valuation.

Despite the modest share of tenants that have seen lease expirations so far, we already observe drastically higher vacancy rates reflecting lease non-renewals and partial renewals among that sample. The contractual occupancy rate in Manhattan, the country's largest office market, was at a 30-year low of 77.8% in the fourth quarter of 2022 (Cushman & Wakefield), as shown in Figure 2 (Panel B).

Figure 3: Lease Expiration Schedule



Notes: The figure shows the percentage of leases expiring per year in square feet for leases that were in force as of December 2019 (left panel) and for leases that were in force as of December 2022 (right panel). Data are sourced from CompStak.

2.4 Impact on Quantities and Prices of New Leases

Pandemic Impact on New Lease Quantities

Next, we investigate the effects of changes in office demand related to the pandemic on the volume of new lease agreements. To do so, we aggregate the total number of new commercial office leases signed in the CompStak data.[5] We observe a dramatic decrease in the quantity of new leases signed, sometimes called absorption in the industry, in the left panel of Figure 4. The volume of newly signed leases fell from 285.38 million square feet (sf) per year in the six months before the pandemic to 62.39 million sf per year over the most recent six months.[6] The graph indicates a large drop in office demand from tenants who are actively making space decisions.

Pandemic Impact on New Lease Duration

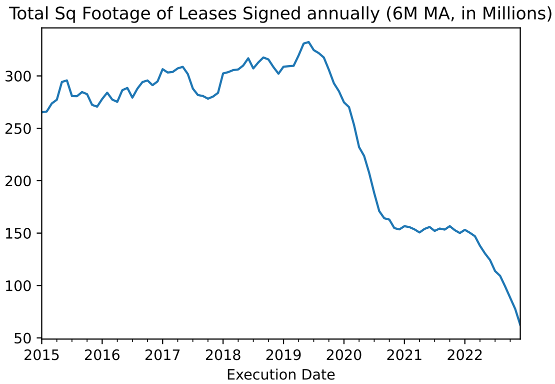
Even when tenants do renew leases, they may not do so under the same set of terms. The right panel of Figure 4 shows that the share of new leases signed that are less than three

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

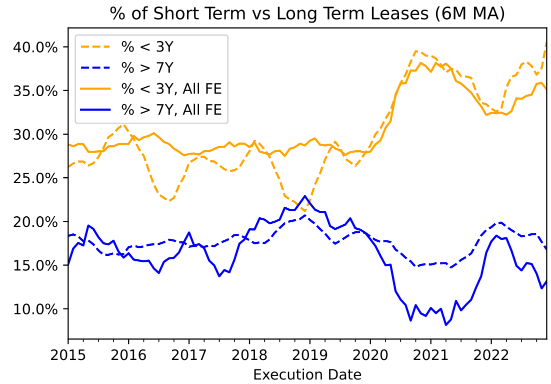
[6]In future data updates, more leases may be added to the data set for the last few months of the sample. Our experience with several such prior data updates is that the revisions are modest.

Figure 4: New Leases Signed and Lease Duration Changes

Panel A: New Leases Signed



Panel B: Lease Duration Changes



Notes: Panel A shows the quantity of leases signed in square feet over time. Panel B shows the share of short-term (less than 3 year duration, in orange) and the share of long-term (more than 7 year duration, in blue) leases over time. Dashed lines denote raw data while the solid lines remove state, major/non-major market, industry, and renewal fixed effects.

years in duration increased substantially during the pandemic, to account for almost half of our sample, while the share of leases with a duration more than seven years decreased meaningfully. The shortening of lease duration suggests important shifts in the commercial office market, even conditional on lease renewal. As a result, the coming years 2023–2025 will feature even larger than expected lease expiration from two channels: the pre-scheduled expiration of long-term leases signed before the pandemic, as well as the expiration of short-term leases signed during the pandemic. The distribution of lease maturities at the end of 2022 is shown in Panel B of Figure 3.

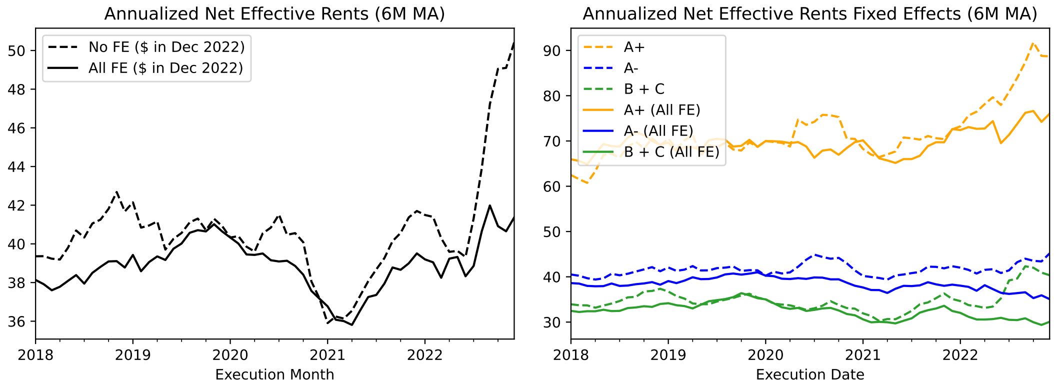
Pandemic Impact on New Lease Rents

We next explore the dynamics of net effective rents on new leases. We compute the square-foot weighted average NER. Figure 5 shows large changes in real NERs on new leases signed over the course of the pandemic. Panel A shows results for for all markets and Panel B subsets on New York City. Nationally, the NER fell by 9.16% in 2020. Starting in January 2021, the NER on newly-signed leases experienced a sharp reversal with the NER ending up back at its pre-pandemic level at the end of our sample.

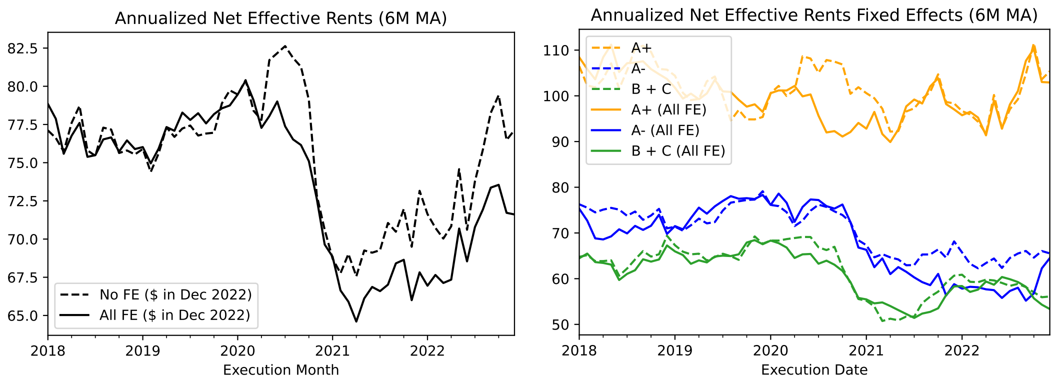
The national average NER dynamics could reflect composition effects, either in terms

Figure 5: Net Effective Rent on New Leases

Panel A: National



Panel B: NYC



Notes: Panel A (Panel B) shows annualized net effective rents for all markets (NYC). Graphs on the left show rents for all building types (in black), while graphs on the right show rents by building class–A+ (in orange), A- (in blue), B+C (in green). Dashed lines denote raw data while solid lines remove state, major/non-major market, industry, and renewal fixed effects. Major markets are defined in footnote 5.

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

In NYC, the NER decline on new leases in 2020 is sharper at 11.55%, and the rebound in 2021 and 2022 is much weaker. The measurement in NYC is less sensitive to the removal of tenant and submarket fixed effects.

2.5 Flight to Quality

Figure 6 highlights the heterogeneity in changes in rents and occupancy across building quality for New York City. The left panels of the graph define class A+ properties based on rent levels.[7] The remaining buildings ("Other") are classes "A-" (A without A+), B, and C. The right panels use an alternative definition of high-quality buildings based on building age: younger buildings are those constructed in or after 2010. Panel A displays changes in NER per square foot on *newly-signed* leases. Properties defined as A+ sustain rent levels much better in both New York 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.

Panel B of Figure 6 shows changes in occupancy, which are the other main driver of revenue. The left panel breaks out trends in occupancy for A+ buildings and others, relative to December 2019. The right panels similarly break out trends in occupancy across buildings of different ages. The clearest expression of quality differentiation occurs in the right panel where the youngest buildings experienced strong occupancy growth while the older buildings struggled to retain tenants.

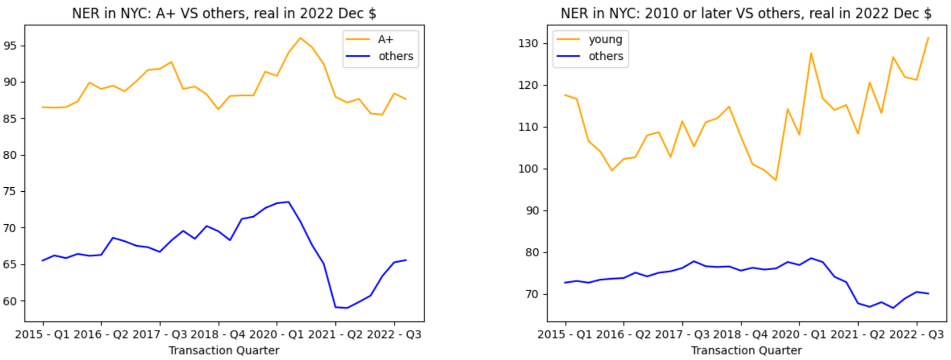
The top right panel of Figure 5 paints a similar picture for the nation as a whole. We focus on the solid lines, which remove fixed effects. Nationally, A+ rents on new leases show resilience, rising modestly between December 2019 and December 2022. Lower-quality office rents, by contrast, see a much steeper decline over the pandemic.

Figure 7 illustrates the flight-to-quality dimension further by plotting the relationship between building age and NER in Panel A for New York and San Francisco leases. The NER is residualized with respect to month, submarket, and tenant fixed effects, so as to control for shifting geographic or tenant composition. It shows that the rent-quality gradient

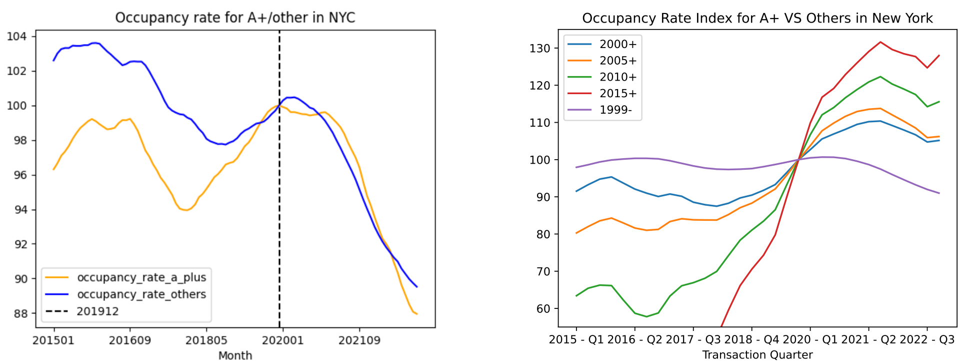
[7] Specifically, we isolate leases that are in the top ten percent of the NER distribution in each quarter and submarket among all properties that are ranked as Class A by CompStak. We categorize a building that has such a lease as A+ and assume that the A+ status remains for ten years, unless another top-10% lease is signed in that building at which point the ten-year clock resets. By this definition, 34.25% of square feet and 41.05% of lease revenue is in A+ office buildings in New York City.

Figure 6: Changes in Office Rents and Occupancy

Panel A: Net Effective Rent by Quality Segment in NYC



Panel B: Occupancy Rates by Quality Segment in NYC



Notes: Panel A shows the annualized NER in December 2022 dollars in NYC. The left panel shows the split by building class (A+ in orange, all others in blue), while the right panel shows the split by building age (built in 2010 or later in orange, all others in blue). Panel B shows occupancy rates in NYC by building class (left), and building age (right).

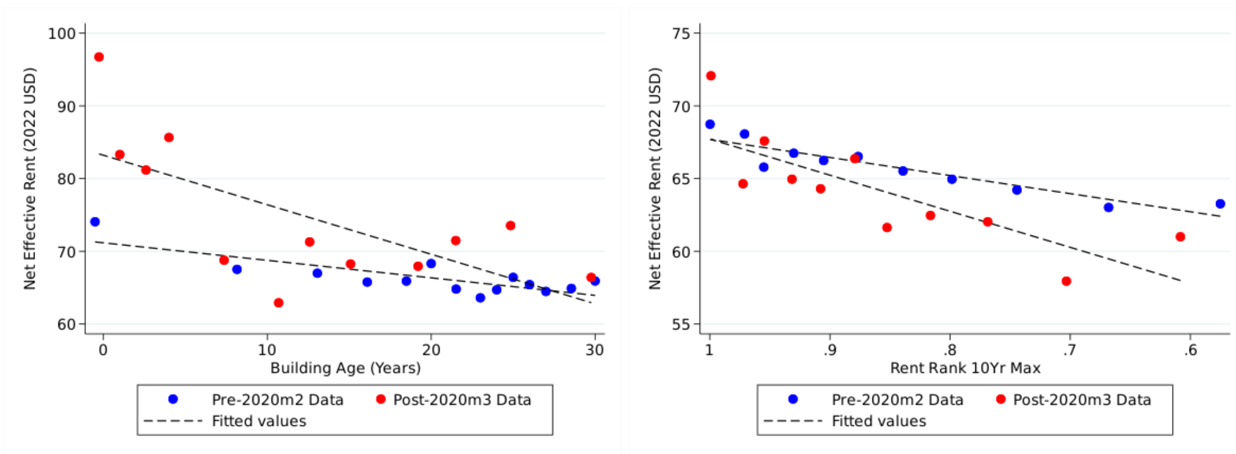
steepens substantially for leases signed in March 2020 or after. Rather than sorting buildings by age, Panel B sorts them by their rent rank, where 0.9 indicates the 90$^{\text{th}}$ percentile of the NER distribution. Again, we find a strong association between building quality and rents in general in the cross-section of building quality (consistent with the general role for filtering as in Baum-Snow and Rosenthal (2022)), but a steeper gradient after the pandemic. Quality becomes a more highly-valued attribute in the recent period.

Appendix Table A1 provides detailed regression evidence confirming the negative relationship between building age and NER, after controlling for month and submarket fixed effects, as well as tenant fixed effects, and even building fixed effects. Rents increase by more in March 2020 or after versus before in young buildings than in old buildings. The additional 2.4% point rent elasticity to age is economically and statistically significant. This

Figure 7: Building Quality and Changes in Rents

Panel A: By Building Age

Panel B: By Building Rent Rank



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

association is largely driven by shifts in major markets, and is particularly strong in New York and San Francisco.

2.6 Connecting Remote Work and Office Demand

While many shifts in the pandemic could have in principle contributed to lower office demand, we identify changes in remote work policies as being critical to this change. Many employers have shifted to rely more on fully-remote workers, while a much larger fraction of employers have instead moved to hybrid work (Bloom, Han and Liang, 2022). Employees are expected to return to the office for some number of days in the week. The implications of hybrid work for office demand are less clear than for fully-remote positions because firms will still require an office presence. That said, firms may have the ability to stagger staff to come into the office on different days or rearrange the workspace to use it more efficiently through the use of techniques such as hot-desking, hoteling, office neighborhoods, and perhaps with the assistance of software.

To examine the role of remote and hybrid work on office demand, we use the Scoop data which estimates firm back to office plans as of the end of 2022 for a sample of over 3,000 firms. We sort these firms by the number of workdays that employees are allowed to be remote in a typical week. While return-to-office plans remain in flux, our classification provides an estimate of firms' expected office plans at a time that they are making important choices on physical footprint. We merge tenants' WFH plans from Scoop with changes in office demand from CompStak, measured as the percentage change in active lease space in square feet from December 2019 to December 2022. Tenants will have a more negative change in office demand if they do not renew leases that come up for renewal during the pandemic or if they renew and take less space.

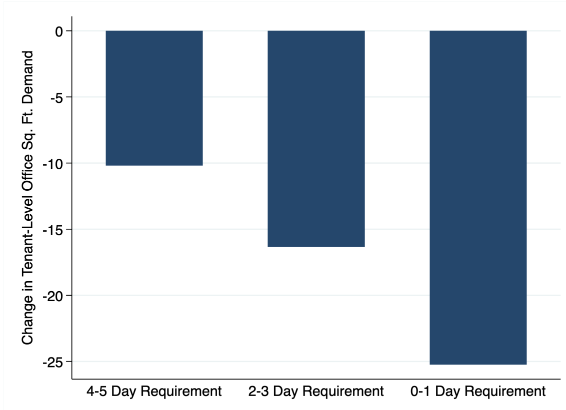
Panel A of Figure 8 shows that hybrid work is strongly associated with lower office space demand. Firm-level office demand drops by 10% for firms whose employees are expected in the office 4 or 5 days per week, by 17% for tenants whose workers will be on site 2-3 days, and by 25% for tenants whose workers are expected to be in the office only 1 day per week or fully remote. The latter decline is likely not even larger because tenants have prior lease commitments that remain in force over the February 2020–December 2022 period over which we compute the change in office demand.

Since firm-level office demand and back-to-office plans may be measured with some error, we also examine the relationship between remote plans and office demand at higher levels of aggregation. We use the tenant industry code to aggregate both tenant office demand and WFH plans to the industry level. Panel B of Figure 8 shows a strongly negative relationship, with industries such as technology that are more remote showing much larger declines in office demand.

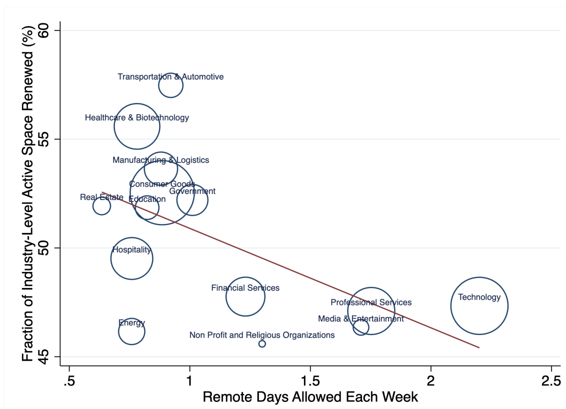
We also examine the relationship between remote working plans and office demand across cities in Panel C. Here, we take advantage of the fact that cities differ in their mix of industries which can be more or less conducive to remote work. We estimate the predicted number of remote working days for each city, based on each city's mix of industries. San Francisco, for instance, has a high predicted number of remote days due to its heavier reliance on the technology industry.

Figure 8: Hybrid Work and Office Demand

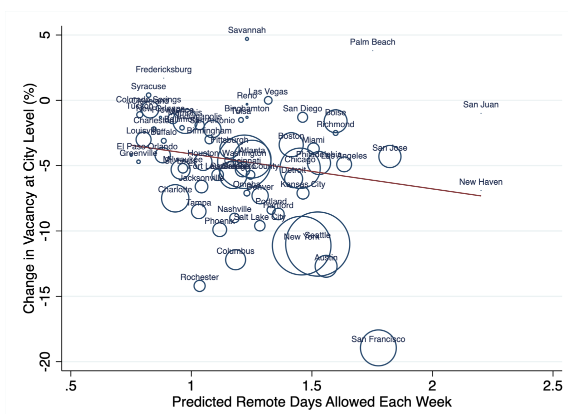
Panel A: Firm Work Mode and Office Demand



Panel B: Industry-Level Remote Work and Office Demand



Panel C: City-Level Predicted Remote Work and Office Demand



Notes: Panel A plots the relationship between firm space demand and stated back-to-work office plans. We measure firm space demand, as elsewhere in the paper, by comparing the firm's total leased square footage in December 2022 against the amount pre-pandemic in December 2019. We then calculate the firm's back to office plans by using Scoop data on firm remote plans. We sort these by assessing how many days a week the firm anticipates workers being back in the office: 0–1 (close to fully remote positions), 2–3 days/week, and 4–5 days a week (including fully in person requirements). Panel B shows the relationship between industry-level remote work and industry-level firm demand, aggregating both the WFH plans and office demand to the industry level. Panel C shows the relationship between city-level remote work predicted based on the city-level industry mix and city-level change in overall occupancy level drawn from Cushman & Wakefield.

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

Table 1 provides numerical estimates which correspond to this figure. At the firm level, in column (1), we find that a unit increase in the remote work index is associated with a ten percentage point decline in square footage at the firm level. Our remote work index is a three point scale, so a one unit increase corresponds to an increase in two days a week remotely for a firm going from 0–1 allowable remote days to 2–3, or from 2–3 days to 4–5 days a week. While these are large economic magnitudes we observe them with greater imprecision.

To partially address the issue of statistical imprecision, we next move to the industry- and city-levels. We estimate, in column (2) of Table 1, that an industry increasing its remote work index by one point (i.e., allowing an additional two days of remote work each week) decreases its overall space demand by eight percentage points.

In column (3), we aggregate remote working plans up to the city-level, and regress this against city-level office occupancy (measured by Cushman & Wakefield). We also find a negative relationship, indicating that more remote work is associated with lower office occupancy. We observe even large magnitudes in column (4), which instruments for city-level remote work using the city's mix of industries. We take each industry's average remote work score, and predict the amount of remote work in each city based on the local industrial composition. San Francisco, for instance, obtains a high predicted remote work score based on its heavy concentration of technology firms. Here, we find that a one-unit increase (two additional remote work days a week) in the remote work index results in a 22 percentage point decrease in office vacancy. This instrumental variable specification helps to address possible endogeneity and measurement error problems in our baseline specification, and suggests a large causal role for remote work in driving trends in office demand, particularly at the city level which we focus on.

Table 1: Remote Work and Office Space Demand

	OLS (1)	OLS (2)	OLS (3)	IV (4)
Remote Work Index (Firm)	-10.11			
	(10.07)			
Remote Work Index (Industry)		-8.28***		
		(2.08)		
Remote Work Index (City)			-4.30	-22.56**
			(3.45)	(10.34)
N	573	14	63	63
Industry FE	Yes	No	No	No
City FE	Yes	No	No	No

Notes: This table shows the relationship between remote work plans and change in office space demand at different levels of aggregation. As elsewhere in the paper, we compare firm's total leased square footage in December 2022 against the amount leased in December 2019. Our remote work index collapses plans into three levels (4–5 days a week in person, 2–3 days a week, and 0–1 days a week). A one unit increase therefore corresponds to allowing two additional remote days a week. Column (1) shows the relationship at the firm level. Column (2) shows the relationship at the industry-level, collapsing average remote work plans and change in office demand to the industry-level. Columns (3)–(4) measure the relationship between remote work plans aggregated to the city level against city-level change in vacancy in the Cushman & Wakefield data. Column (4) instruments for the city-level remote work index using the predicted remote work level based on industrial composition. All specifications weight observations based on office space for firms, industries, and cities, respectively. Standard errors in column (1) are clustered at the city-level.

As an alternative measure of firms' WFH plans, we measure the fraction of a firm's job listings that are for fully-remote positions from Ladders. Table A2 finds a negative and significant relationship between a tenant's change in office demand and the fraction of that tenant's job postings that are for remote positions. A 10% point increase in the share of remote job postings lowers office demand by 3.9–4.9% points. This result is consistent with the idea that durable shifts in remote work are changing the demand for office space.

Combined, our empirical results show that office space demand has declined considerably over the course of the pandemic and that changes in remote work policies appear to be driving this trend. Firms with more fully-remote positions or that have low on-site work requirements experience the largest declines in office demand. Decreases in office demand are still substantial among firms with hybrid back-to-office plans, suggesting that even hybrid work plans pose major disruption to aggregate office demand, with significant implications for aggregate office values.

3 Office Valuation Model

How do changes in remote work and the accompanying changes in office rent revenues affect the value of office buildings? To answer this important question, we develop a valuation model. The value of a building (or portfolio of buildings or the market overall) is the expected present discounted value of rent revenues Rev_{t+j} minus expenditures $Cost_{t+j}$:

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

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

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

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

3.1 Modeling Revenues

The central challenge in modeling leases is incorporating the process of expiration and lease renewal, at potentially different lease rates. This is important because commercial leases are long-term in nature, but much shorter in duration than the expected life of the building. In our model, leases 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 us from having to keep track of the history of past lease executions. Under this assumption, we only need two state variables to describe the evolution of rental revenues in a building/market: $\widehat{Q}^O_t$ and $\widehat{R}^O_t$.

Let Q^O_t be the occupied space (in square feet) in a building/market at the end of period t and Q^V_t 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 $Q^V_t = \overline{Q}_t - Q^O_t$. The law of motion for occupied space in a building/market is:

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

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

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

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

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

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

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

with the law of motion:

$$\widehat{Q}^O_{t+1}(\hat{Q}^O_t, z') = \min\left\{ \frac{\widehat{Q}^O_t(1-\chi) + \widehat{Q}^O_t \chi s^O_{t+1}(z') + (1-\widehat{Q}^O_t) s^V_{t+1}(z')}{1+\eta_{t+1}(z')}, 1 \right\}. \tag{2}$$

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

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

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

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

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

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

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

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

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

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

The law of motion for the scaled state variable becomes:

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

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

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

Define potential rent as the rent revenue based on full occupancy at the prevailing market rent: $\overline{Q}_t R_t^m$. Denote the rent revenue scaled by last period's potential rent with a hat:

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

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

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

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

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

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

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

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

3.2 Modeling Costs

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

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

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

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

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:

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

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

Recall the expected PDV of costs V_t^C:

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

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

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

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

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

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

Bellman equations (4) and (5) have closed-form solutions spelled out in Appendix 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. While risk and return are likely to vary across space, we focus here on New York City: America's largest office market. One key parameter will be identified from the A+ segment of the NYC office market, so we also need a separate calibration for that segment of the NYC office market. We then repeat the calibration exercise for two more cities: San Francisco and Charlotte. The former is affected even more severely by remote work than NYC, while the latter is affected less severely.

3.3.1 States and State Transition Probabilities

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

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

[8]We can think of the two non-WFH states, E and R, as states where there was a small amount of work done from home. American Time Use Survey data for 2017 put the fraction of remote work at around 5%. Conceptually and computationally, the model can easily accommodate more remote work states. However, this would lead to a parameter proliferation that creates difficulties for calibration.

sumed to be independent:

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

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

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

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 $\mathbf{q} = 5\%$, to capture the idea that a transition to mass adoption of remote work was unlikely before 2020. The second parameter is the probability of remaining in the WFH state conditional on having entered it, which we label $\mathbf{p}$. The latter governs the persistence of remote work, and it is a key parameter of interest in the paper. We will infer the value of $\mathbf{p}$ from the observed change in class A+ office valuations at the onset of the pandemic, as measured from office REIT data, and perform robustness with respect to this parameter. As explained in detail below, this calibration delivers $\mathbf{p} = 0.9446$. These two parameters pin down $\pi^{WFH}(z'|z)$:

$$\pi_{WFH} = \begin{array}{r} \\ \text{No WFH} \\ WFH \end{array}\!\!\begin{array}{c} \begin{array}{cc} \text{No WFH} & WFH \end{array} \\ \begin{bmatrix} 1-q & q \\ 1-p & p \end{bmatrix} \end{array} = \begin{array}{r} \\ \text{No WFH} \\ WFH \end{array}\!\!\begin{array}{c} \begin{array}{cc} \text{No WFH} & WFH \end{array} \\ \begin{bmatrix} 0.95 & 0.05 \\ 0.0554 & 0.9446 \end{bmatrix} \end{array}.$$

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 both expansions and recessions. First, we match the risk-free rate, conditional on being in a given state:

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

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

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

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

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

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

The SDF component $M^{WFH}(z'|z)$ governs how the risk associated with working from home is priced. It is chosen to price the returns on a portfolio of stocks that goes long companies that benefit from remote work and short companies that are hurt by remote work. We deliberately exclude real estate stocks from the portfolio. Appendix B2 contains the details of the WFH factor construction. We call this portfolio the WFH equity factor.

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

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

We estimate the (conditional) stock and bond betas in the December 2014–December 2019 period. Appendices B4 and B5 show how we pin down the (conditional) market prices of risk for the WFH equity risk factor, and for the stock and bond risk factors, respectively. Given our value of $\lambda^{wfh} = -7.0\%$, we find $Ret^{wfh}(z' = \text{no WFH}|z = \text{No WFH}) = -6.42\%$.

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

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

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

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

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

$$M^{WFH,unscaled} = \begin{array}{r} \\ \text{No WFH} \\ WFH \end{array} \begin{array}{c} \begin{array}{cc} \text{No WFH} & WFH \end{array} \\ \begin{bmatrix} 1 & 1.696 \\ 1 & 1.696 \end{bmatrix} \end{array}, \quad M^{WFH} = \begin{array}{r} \\ \text{No WFH} \\ WFH \end{array} \begin{array}{c} \begin{array}{cc} \text{No WFH} & WFH \end{array} \\ \begin{bmatrix} 0.966 & 1.639 \\ 0.627 & 1.080 \end{bmatrix} \end{array}.$$

The model considers the WFH state (second column) to be a worse state of the world—with a higher market price of risk—as the no-WFH state (first column). Assets such as offices, that have lower returns in that state of the world, are therefore riskier. Note that even if the WFH state is otherwise positive for productivity, it may require high investment, resulting in higher marginal utility of consumption (Papanikolaou, 2011). As a robustness check, we redo the valuation exercise switching off priced WFH risk by setting M^{WFH} to a matrix of ones.

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

3.3.3 Office Cash Flows for All NYC

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

We set the lease expiration parameter at $\chi = 0.14$. This delivers a lease duration of 7.32 years, matching the CompStak average office lease term in the New York City data. Table 2 lists the remaining parameters, which vary by state.

Market NER growth ϵ in expansions and recessions comes from the January 2000 to December 2019 CompStak data.[9] NER is strongly pro-cyclical. Market NER growth in the remote work state comes from the December 2019 to December 2022 CompStak data. Mar-

[9]When constructing market NER time series, we control for submarket, tenant industry, leasing type, and building class FEs and then apply 6-month moving average to the raw series. Since NBER business cycles in this period (and before) are shorter than commercial real estate leasing cycles, we use the latter to determine the values for annual NER growth in expansions and recessions. Strict adherence to NBER dates would result in office NER growth that is too similar across expansions and recessions, and make the large fluctuations in rent growth observed in the data highly unlikely events from the perspective of the model.

Table 2: Calibration for All NYC

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0603	-0.1173	0.0245	-0.1289
Supply growth	η	-0.0141	-0.0147	-0.0254	-0.0260
Lease renewal share	s^O	0.8545	0.3117	0.4066	0.1483
New leasing share	s^V	0.1848	0.3391	0.0879	0.1614
Fixed cost/rent ratio	c^{fix}	0.2000	0.2000	0.2000	0.2000
Variable cost/rent ratio	c^{var}	0.2300	0.2300	0.2300	0.2300
Leasing commission new	LC^N	0.3000	0.3000	0.2400	0.2400
Leasing commission renewals	LC^R	0.1500	0.1500	0.1200	0.1200

ket NER growth was -12.89% from December 2019 to December 2020 (one WFH-R year), and 2.45% per year from December 2020 to December 2022 (two WFH-E years).

Supply growth $\eta(z)$ incorporates new construction net of depreciation and reductions in office space due to conversion to alternative use. The values for supply growth for expansion and recession periods are calculated from CompStak based on the year of construction of all office buildings. New construction is 1.15% in expansions and 1.10% in recessions. We subtract a 2.56% depreciation rate, a realistic number for office property, from the new construction numbers to arrive at the net supply growth η reported in the table.[10] Supply growth is acyclical because of the long construction lags for office properties.

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

The parameters $s^O(E), s^O(R), s^V(E), s^V(R)$ govern office demand across the business cycle in the non-WFH states. We pin down these four parameters to match four moments of the NYC contractual occupancy rate over the period 1987.Q1–2019.Q4, plotted in panel B

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

of Figure 2. Those moments are the mean, the standard deviation, the maximum, and the minimum. The resulting lease renewal share for existing leases that are up for renewal, s^O, is strongly pro-cyclical. The new leasing share for vacant space, s^V, is counter-cyclical, simply because there is much less vacant space available for lease in expansions. This calibration ensures that our model matches both the average vacancy rate of NYC office as well as the amplitude of the leasing cycle, which reflects cyclical tenant demand for office.

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

$$s^i_{z,wfh} = \delta \cdot s^i_z, \qquad z = E, R, \ \ i = O, V. \tag{6}$$

We estimate δ to best fit the dynamics of the office occupancy rate over the 12 quarters from 2020.Q1–2022.Q4. Appendix D explains the details. The resulting value is $\delta = 0.48$, which indicates a large downward shift in office demand in the WFH state. This shift is consistent with the evidence on the large decline in new leasing activity, documented in Figure 4.

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

3.3.4 Office Cash Flows for A+ Properties in NYC

Next, we calibrate the model to A+ buildings of New York City. We use the leases on the subset of A+ buildings to get parameter estimates for the A+ NYC office sector. The calibration approach parallels that for All NYC, and is detailed in Appendix D. χ is set to be 0.12 to match the slightly higher average lease duration of 8.06 years of A+ leases in NYC.

Appendix Table E1 lists the remaining parameter estimates for the A+ universe. The cost parameters are assumed to be the same as for the market as a whole.

3.4 Identifying the Persistence of Work From Home

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

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

Figure 9 plots this model-implied realized return on A+ office in this transition, the left-hand side of the equation above, for a range of values of $\mathbf{p}$.[11] Since the office return in this transition varies strongly with $\mathbf{p}$, this moment is well-suited to identify this parameter.

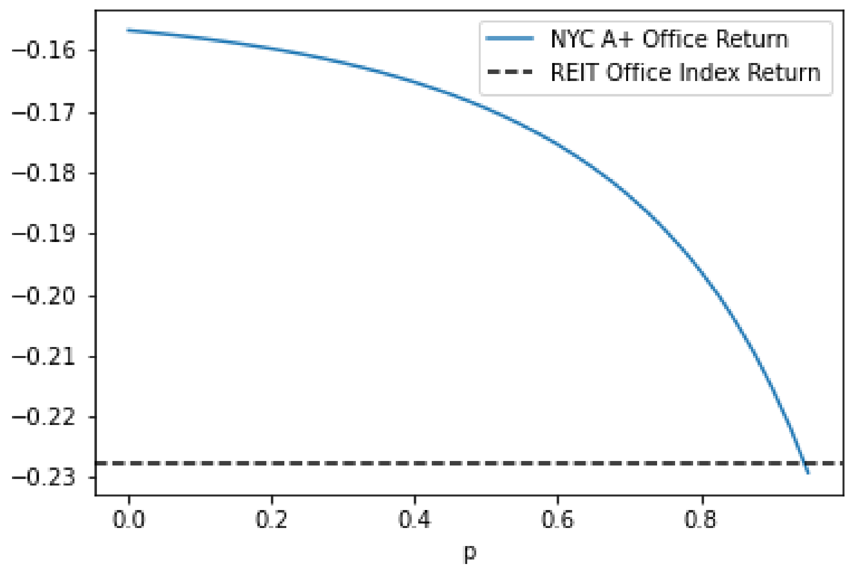
In order to pick the relevant point on this curve, we turn to the REIT data. REITS invest in class A+ office properties. The three NYC-centric office REITs, (SL Green, Vornado, and Empire State Realty Trust), experienced a value-weighted return of -36.16% between December 2019 and December 2020. After unlevering this equity return, the asset return was -22.75%.[12] The model matches this decline for a value of $\mathbf{p} = 0.94$. With this key parameter identified, we can return to the calibration for the full NYC office market and calculate the change in its value due to remote work.[13]

[11] 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.

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

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

Figure 9: Determining **p** by Matching Realized Return of A+ Market



4 Office Valuation Results

4.1 Key Model Outcomes

Table 3 presents the model solution for the "All NYC" office calibration. The model delivers a reasonable unconditional average cap rate of 7.28% for the overall NYC office market. The cap rate is 9.23% in recessions and 7.05% in expansions.[14]

In a Gordon Growth Model with constant expected NOI growth rate g and a constant discount rate r, the cap rate $c = r - g$. Our Markov Chain model features time-varying expected growth and time-varying expected office returns, so this relationship does not hold. It is nevertheless useful to look at the two components of the cap rate. The model implies an expected return on NYC office of 7.01% and an office risk premium of 5.52%. This is naturally lower than the equity risk premium of 7.98% since an unlevered office property

conservative. One could also use our procedure to update the implied persistence parameter over time.

[14]The hedonic-adjusted cap rate for Manhattan Office averaged 5.3% over the period 2001–19 according to Real Capital Analytics data. The model predicts a 5.47% average cap rate for the same period. Longer, national data from CBRE put the average office cap rate for NYC at 7-8%, close to our model's steady-state. Like the model, the Real Capital Analytics data indicates higher cap rates in recessions (6.0% in 2001, 2008, 2009) than in expansions (5.2% for 2002–2007 and 2010–2019).

Table 3: Model Solution for NYC All Calibration

Statistic	Uncond	E	R	WFHE	WFHR
R_f	0.0149	0.0084	0.0467	0.0084	0.0467
Equity $\mathbb{E}[Ret] - 1$	0.0947	0.0773	0.1846	0.0746	0.1815
Equity RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0798	0.0690	0.1379	0.0662	0.1348
Cap rate	0.0728	0.0705	0.0923	0.0668	0.0920
Office $\mathbb{E}[Ret] - 1$	0.0701	0.0619	0.1522	0.0487	0.1225
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0552	0.0535	0.1054	0.0404	0.0757
$\mathbb{E}[g_t]$	-0.0037	-0.0113	0.1383	-0.0473	0.0849
Vacancy rate $= 1 - \widehat{Q}^O$	0.2121	0.1031	0.1591	0.3216	0.3241
$\widehat{\text{Rev}}$	0.7373	0.7906	0.8883	0.6391	0.7556
$\widehat{\text{Cost}}$	0.3984	0.4273	0.4152	0.3688	0.3685
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.3389	0.3632	0.4731	0.2702	0.3870
$\widehat{V}^R$	8.4092	9.5096	8.5116	7.4721	6.9610
$\widehat{V}^C$	3.8292	4.4084	3.4498	3.4900	2.8195
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	4.5800	5.1012	5.0619	3.9821	4.1414

is less risky that the aggregate stock market (which is a levered investment). The office risk premium is substantially higher in recessions (10.54%) than in expansions (5.35%).[15]

Expected NOI growth is close to zero (-0.37% per year) unconditionally. This number is in real terms and incorporates that the office stock depreciates at 2.56% per year, so that real NOI growth is 2.20% 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 21% on average, higher in recessions than expansions by 5.60% points, and much higher conditional on being (and remaining) in the remote work states, around 32.2%.

The last part of the table shows the value of the building, scaled by potential rent, and broken down into the PDV of revenues minus PDV of costs. The typical NYC office trades for a multiple of 4.58 times potential gross rent unconditionally according to our calibration.

[15] The model has interesting implications for the term structure of office risk premia discussed in Appendix G1.

The average valuation ratio of office properties in the no-WFH expansion state of 5.10 is 23.17% higher than the value of 4.14 in the WFH-R state. Appendix Figure D1 shows the valuation ratio for office $\widehat{V}$ conditional on expansion, recession, WFH-expansion and WFH-recession for NYC.

4.2 The Effect of WFH on Office Values

4.2.1 Entire Office Stock

To assess the effect of remote work on office values, we let the economy undergo the same transition as the one we considered for A+ office when calibrating the parameter $\mathbf{p}$, 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 (2) and (3) under the "All NYC" calibration. The model captures the decade-long expansion before the Covid-19 pandemic. We then apply the law of motion once more to obtain $(\widehat{Q}^O_{20}, \widehat{R}^O_{20})$ assuming the economy transitioned from E to WFH-R between 2019 and 2020.

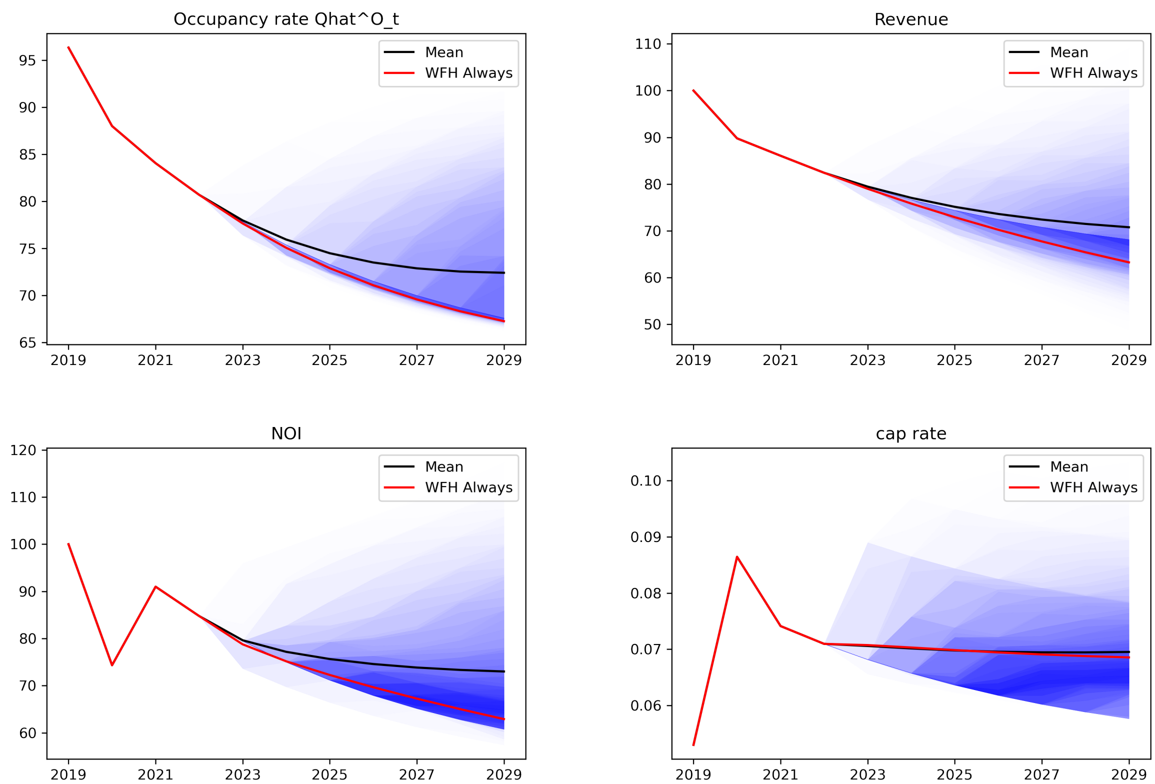
The realized growth rate of potential gross rent in this transition is -15.14% in the model. The change in the scaled valuation ratio is -36.43%. Therefore, the overall value of the NYC office stock in this transition falls by 46.06%:

$$\left(\frac{\widehat{V}(\widehat{Q}^O_{20}, \widehat{R}^O_{20}, WFHR)}{\widehat{V}(\widehat{Q}^O_{19}, \widehat{R}^O_{19}, E)}\right)\left(\frac{\overline{Q}_{20}R^m_{20}}{\overline{Q}_{19}R^m_{19}}\right) = (1-36.43\%)\cdot(1-15.14\%) = (1-46.06\%).$$

Put differently, if the entire office stock of NYC had been marked-to-market, its value would have fallen by 46.06% in 2020. This same decline is 26.66% 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. In the third year (2022), and it stays in the WFH-E state. From 2023 onward, we let the economy evolve stochastically according to its laws of motion governed by π. Since there are many possible paths for the evolution of the state, Figures 10 and 11 show fan charts where darker blue colors indicate more likely future paths. The solid black line indicates the mean path. The red line plots the average path conditional on the economy remaining in the WFH state every year until (at least) 2029. The probability of this event occurring is 67.11% according to the model.

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



Notes: The graph shows the evolution of the valuation ratio $\widehat{V}$ for a transition from expansion in 2019 to WFH-R in 2020, WFH-E in 2021 and 2022. From 2023 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 96.33% in 2019 to a value of 80.68% in 2022. In the data, there is a similar decline from 88.9% in 2019.Q4 to 77.8% in 2022.Q4. Since long-term leases continue to roll off and renew at low rates as long as the economy is in the WFH state, the decline in occupancy is protracted.

Should the economy remain in the WFH state until 2029, occupancy would eventually fall below 70% even after accounting for the supply response.[16]

Lease revenues, in the top right panel, reflect the protracted decline in occupancy and the gradual repricing of existing leases at lower market rents. The model predicts a decline in active lease revenues ($Q^O R^O$) of 17.58% between 2019 and 2022, which is close to the observed decline in active lease revenues in the CompStak data for New York City of 15.54% between December 2019 and December 2022. Lease revenues go down 29.23% by 2029 along the average path. They fall by an additional 10% points for the red line, reflecting the faster reduction in the overall quantity of office space if the economy remains in the WFH state for longer.

The bottom left panel shows that NOI falls by less than revenues since costs also decline in occupancy. The bottom right panel shows that office cap rates were below 5.30% in 2019 in the model, after a decade-long expansion that increased occupancy and rents. Cap rates then increase in 2020, fall back in 2021 as the economy shifts from recession to expansion, and then gradually stabilize toward their unconditional mean of 7.28%.

The combination of declining cash flows and rising cap rates results in a substantial change in the value of office V_t, shown in Panel A of Figure 11. The graph illustrates a mean path that sees no recovery. Remote work is a near-permanent shock. Ten years after the transition, office values remain at levels that are 43.87% 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.[17] 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 51.58% lower in 2029 than in 2019.

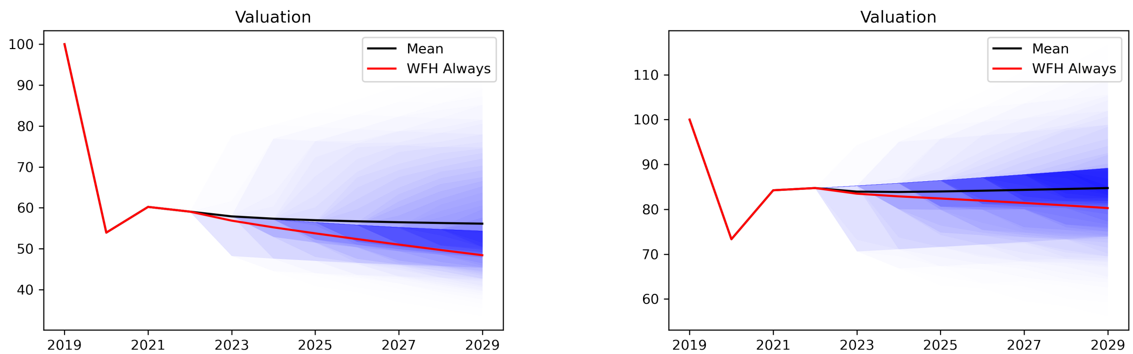
A second key message from the valuation exercise is that there is substantial uncertainty

[16] Recall that supply growth in the WFH state is 1.13% points lower per year in the WFH than in the no-WFH states. This captures reduced construction as well as conversion of office to alternative use.

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

Figure 11: Office Valuation Distribution,

Panel A: All NYC Panel B: NYC A+ Buildings



Notes: The graph shows the evolution of the office value V for a transition from expansion in 2019 to WFH-R in 2020, WFH-E in 2021 and 2022. Values are normalized to 100 in Dec 2019. From 2023 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. Panel A shows the distribution of values for all NYC office buildings; Panel B focuses on A+ office value (buildings with a lease in the top ten percentile of the rent distribution in their submarket in the last ten years).

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 do a separate valuation exercise for the A+ segment, which has its own cash-flow parameter calibration to the A+ data as defined in Section 2. The resulting parameters and the model output for cap rates, valuation ratios, and vacancy rates are reported in Appendix E. They show lower cap rates and lower expected returns in the A+ segment, consistent with the lower risk of this segment.

Panel B of Figure 11 revisits the transition graph for office values. It shows substantially smaller value reductions both in the short- and in the long-run. The mean path has office values down by 15.26% 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 19.72%. The better performance is due to the stronger rent growth for A+ in the WFH states, and a lower risk premium for A+ office especially in the WFH state.

On the flip side, the performance of the A-/B/C-class office segment (the complement to A+) is strictly worse than the overall market. Its initial value decline is -70.37% compared to -46.06% for all office.

4.3 Other Office markets and Aggregate Impact

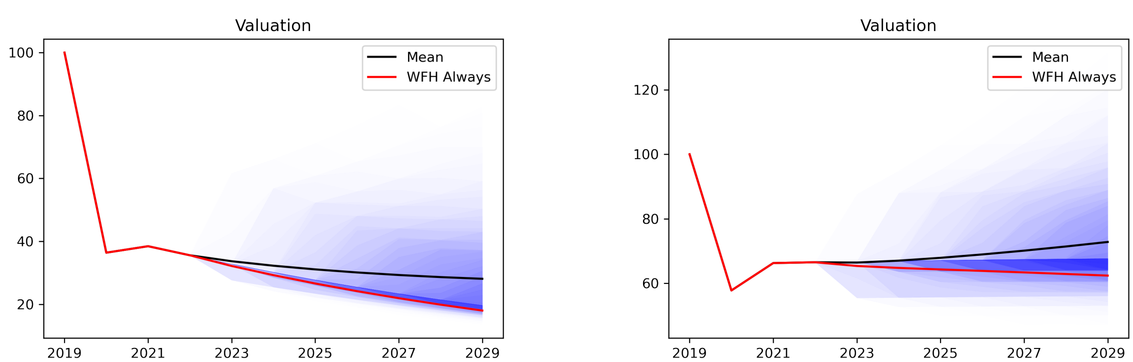
4.3.1 San Francisco and Charlotte

We repeat the valuation exercise for San Francisco (SF) and Charlotte. Appendix F discusses the calibration and reports the resulting valuation moments. Figure 12 below shows the main fan chart for the valuation of the stock of SF office (left panel) and Charlotte office (right panel). The short-run (long-run) declines in office values are 61.55% (71.90%) for SF and 33.70% (27.16%) for Charlotte. The former are larger than for NYC, due to the more cyclical nature of the SF office sector and its larger WFH exposure. This is consistent with SF's larger exposure to tenants from the technology sector who have more eagerly embraced remote work. Charlotte's valuation effects are smaller than NYC due to its milder office cycles and smaller exposure to the WFH shock. Adjusted for market coverage, the total office value destruction between the end of 2019 and 2022 is \$32.7 billion in SF and \$5.1 billion in Charlotte.

Figure 12: Office Valuation Changes for Other Cities

Panel A: San Francisco

Panel B: Charlotte



Notes: The graph shows the evolution of the office value V for a transition from expansion in 2019 to WFH-R in 2020, WFH-E in 2021 and 2022. From 2023 onward, the state evolves stochastically. Office values are normalized to 100 in Dec 2019. The shaded areas show percentiles of the distribution of simulated paths, with the darkest color indicating the 40–60 percentile range, and the lightest color the 10–90 percentile range. Panel A shows results for San Francisco, and Panel B shows results for Charlotte.

4.3.2 Aggregate Impact

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

Table 4: Cross-Sectional Results For Top 20 Markets

State	Market	(1) Active SF (mi)	(2) Lease Rev Chg	(3) New SF Chg	(4) NER Chg	(5) Value Chg	(6) Coverage (%)	(7) Value Chg Scaled
NY	New York	290.20	-15.54	-43.15	-8.41	-51.20	73.58	-69.58
CA	San Francisco	61.52	-18.55	-62.78	-31.99	-20.35	62.14	-32.75
NC	Charlotte	23.67	-1.33	-88.44	-8.06	-2.43	47.54	-5.11
DC	Washington DC	88.72	-27.09	-78.31	-16.11	-14.19	98.81	-14.36
CA	Los Angeles	72.33	-26.36	-93.25	-43.79	-10.64	42.83	-24.84
MA	Boston	57.42	-12.03	-34.65	9.75	-7.85	35.33	-22.22
IL	Chicago	90.29	-21.66	-91.22	-13.54	-6.25	43.25	-14.45
WA	Seattle	41.14	-18.35	-81.50	-21.34	-4.15	36.10	-11.50
GA	Atlanta	41.97	-15.45	-85.26	-23.08	-3.23	31.33	-10.31
TX	Dallas	46.34	-25.64	-73.18	-4.35	-3.92	26.60	-14.74
CA	Orange County	39.26	-26.87	-94.08	3.68	-3.96	47.36	-8.36
CA	San Diego	29.41	-21.95	-94.85	-28.50	-3.42	42.11	-8.12
TX	Houston	42.12	-39.46	-100.00	nan	-4.25	28.63	-14.85
VA	Arlington	26.11	-31.46	-66.63	-4.79	-3.75	36.10	-10.39
CA	Palo Alto & Sunnyvale	14.94	3.29	-87.23	-32.87	-1.59	36.10	-4.40
CA	San Jose	22.07	-17.99	-85.82	-23.45	-2.77	11.39	-24.32
TX	Austin	27.97	-14.30	-80.54	-8.60	-2.27	54.54	-4.16
CO	Denver	28.81	-21.12	-88.07	-26.26	-2.17	29.78	-7.29
PA	Philadelphia	26.45	-18.87	-75.06	-4.68	-1.97	23.24	-8.48
NJ	North Jersey	17.51	-14.61	-21.22	-35.09	-1.59	18.29	-8.69
Top 20 (Compstak)		1088.28	-18.67	-71.68	-3.87	-151.94	41.26	-318.93
Other markets (Compstak)		927.86	-18.17	-83.70	-6.13	-67.64	36.10	-187.39
U.S. (Compstak)		2016.14	-18.51	-78.14	1.61	-219.58	38.87	**-506.31**

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

Column (5) calculates the change in office values between December 2019 and December 2022 (in December 2022 dollars). It combines the size of the market in column (1), the change in lease revenues reported in column (2), and the change in the value-to-revenue ratio from the model. For NYC, San Francisco, and Charlotte, we calibrated the model separately, delivering a valuation ratio change that is market-specific. The three-year value destruction is \$51.2 billion for NYC, \$20.4 billion for San Francisco, and \$2.4 billion for Charlotte. For the other 17 large office markets, we use the market-specific size and leasing revenue change in columns (1) and (2) and combine them with the valuation ratio change for NYC to arrive at column (5). Summed across the top-20 markets, we obtain a \$151.9 billion value loss. Extending the analysis to the remaining 85 office markets, we find an additional \$67.6 billion in value destruction for a total of \$219.6 billion across all 105 markets in the CompStak data.

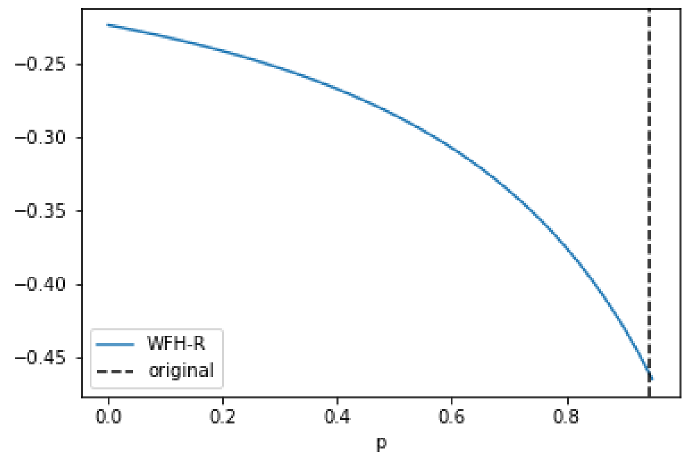
CompStak does not provide universal coverage. Based on Cushman and Wakefield reports, we are able to obtain a December 2019 coverage ratio estimate for 18 of the top-20 markets, shown in column (6). A coverage ratio of 36.1% for the remaining 87 markets (=105-18) reconciles the total U.S. office inventory in CompStak to that in Cushman & Wakefield. To obtain our aggregate value impact statistic in column (7), we divide column (5) by column (6). We arrive at an aggregate \$506.3 billion loss in office values nationwide over the 2019–2022 period. The largest dollar losses are in NYC (\$69.6) and SF (\$32.7), followed by Los Angeles and San Jose.

4.4 Sensitivity Analysis

We conduct several robustness checks. First we explore sensitivity to the WFH persistence parameter $\mathbf{p}$. Figure 13 plots the NYC office value decline in 2020. The vertical dashed line indicates our benchmark model with $\mathbf{p} = 0.94$, which produces a 46.06% valuation decline in the transition. This same decline is around 28.04% for a value of $\mathbf{p}$ that is half as large as our benchmark.

Next, we study sensitivity to another important parameter: rent growth in the WFH-R state. That parameter is hard to pin down since we have only observed one realization of that state. Figure G2 shows that setting NER growth in the WFH-R state equal to that in

Figure 13: Change in Valuation with Different **p** for All NYC



the R state, a natural alternative, has only minimal effect on office values compared to the benchmark. This result suggests that our results are not driven by poor office realizations in 2020 itself.

WFH affects office values through both cash flows and discount rates. We conduct an exercise where we shut off the WFH discount rate channel (M^{WFH} equals the identity matrix). Figure G3 shows that the office value decline is only slightly smaller, so that most of the valuation impact comes from lower current and future cash flows and business cycle risk.

Finally, Figure G4 performs four sensitivity analyses for San Francisco office values to (i) rent growth in the WFH-E state, (ii) the reduction in supply growth in the WFH states, (iii) the persistence of remote work, and (iv) the introduction a floor for office values as a simple way to model additional optionality arising from adaptive reuse (not already captured by the net supply parameter η). The persistence parameter and the supply gap have the largest impact on valuations.

5 Discussion and Conclusion

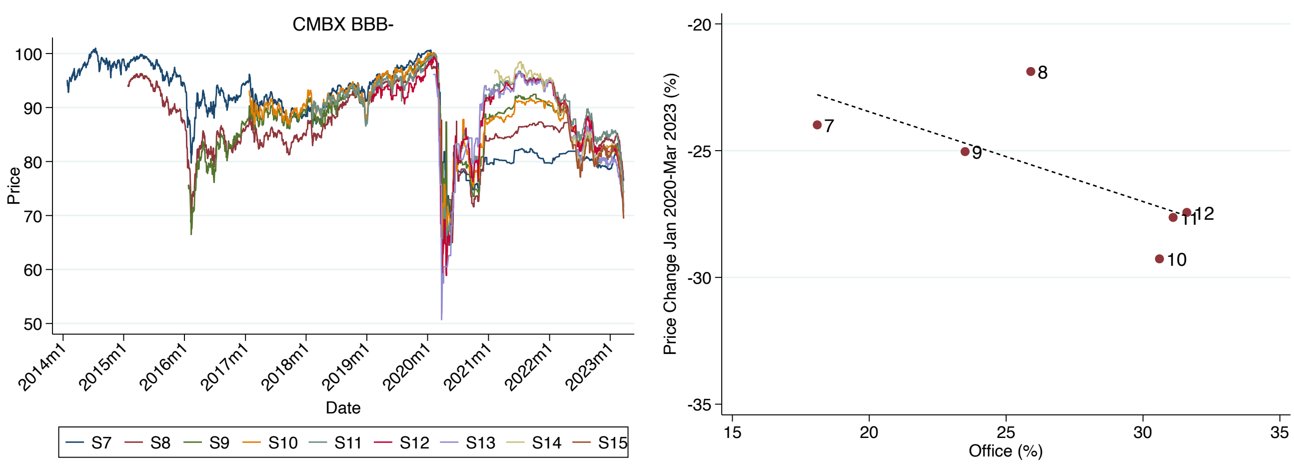
The real estate sector provides a unique vantage point to study the large social shifts in the wake of the Covid-19 pandemic. We estimate a 46.1% decline in the value of New York

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 43.9% below pre-pandemic levels. The numbers for NYC are not an outlier; we find similar effects across many of the largest office markets. Our novel commercial real estate valuation model is suitable for calibration to office markets in other locations, other commercial real estate sectors, and other real assets.

These valuation changes are large, but since about 80% of the office stock is privately-held and private transactions have been few and 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 recently, as shown in Figure 14.

Figure 14: Price of CMBX Insurance and Office Exposure



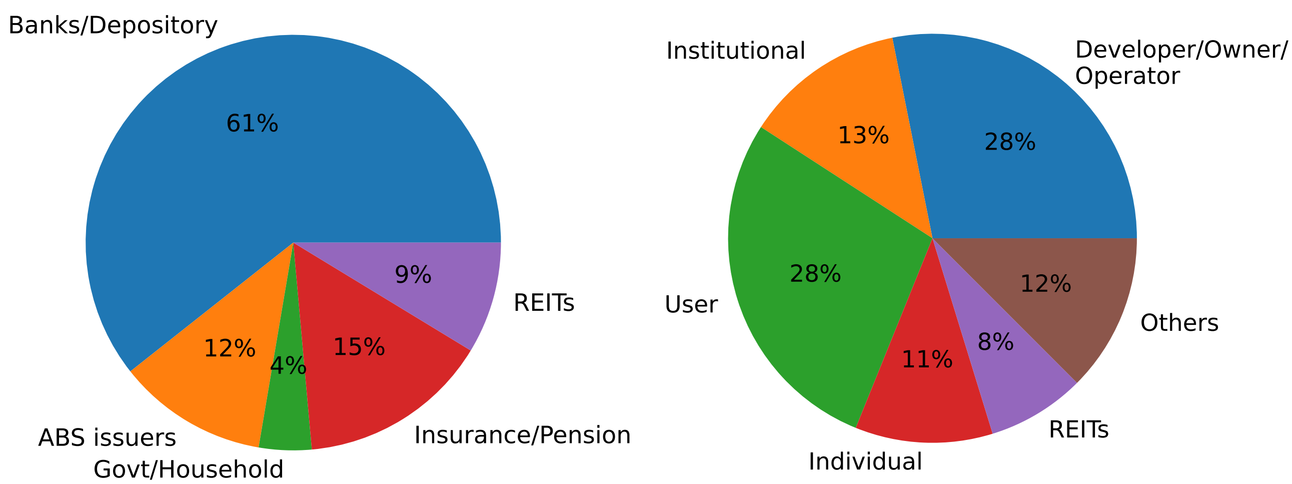
Panel A: CMBX Prices

Panel B: Office Exposure

Notes: Panel A shows prices for the Markit CMBX index of credit default insurance for BBB- tranches. A price of $60 implies that a pool without early prepayments or defaults requires an upfront payment of roughly $40 per $100 original notional to initiate a trade purchasing protection against default. The different lines are for different vintages, denoted S7 through S15. Panel B plots the share of mortgages in each vintage that is backed by office properties against the price change of the CBMX BBB- tranche between January 2020 and March 2023.

The predicted substantial decrease in office values, particularly for lower-quality offices, would impact not only the equity but also the debt under a standard pre-pandemic capital structure. As depicted in the right panel of Figure 15, ownership of office property equity is widely spread among various investor types. Debt ownership, shown in the left panel, is more concentrated with banks holding over 60% of all CRE debt.

Figure 15: CRE Debt and Equity Ownership



Panel A: Debt Ownership (All CRE, 2022) Panel B: Equity Ownership (Office, 2020)

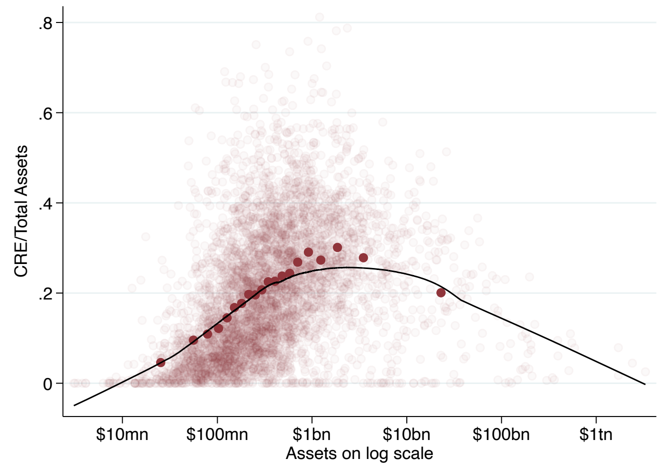
Notes: Debt ownership data is from the Federal Reserve Flow of Funds data and office ownership is from Real Capital Analytics.

A large proportion of banks' loan books is comprised of commercial real estate debt. Figure 16 shows that this particularly true for medium-sized banks (Table A3 gives more detail). CRE credit risk compounds the negative impact of higher interest rates on bank equity, increasing the risk of financial fragility especially among regional banks (see also Jiang, Matvos, Piskorski and Seru, 2023, for recent work on this important topic).

Finally, the decline in office values and the surrounding 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 property taxes in NYC's budget was 48% in 2021, 31% of which comes from office and retail property taxes.[18] A 43.9% decline in property

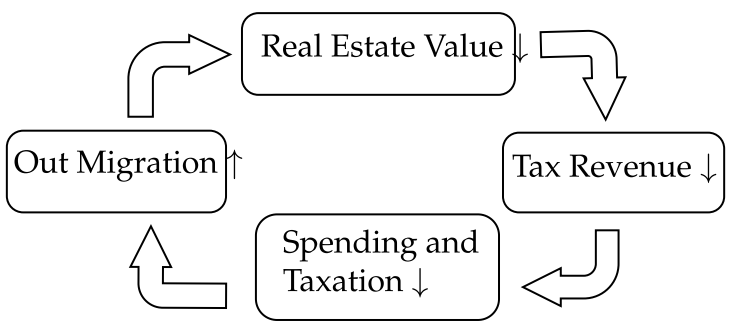
[18] An additional 3% of tax revenue comes from a tax on real estate tenants, and there are further indirect effects on sales and income tax from weakness in CBD office and retail. Office property tax collection alone exceeds the combined budgets of Sanitation, Fire, Transportation, and Parks and Recreation departments in NYC.

Figure 16: Commercial Real Estate By Bank Size



Notes: Data are from 2020.Q4 Bank Call Reports.

Figure 17: Repercussions of Commercial Real Estate Valuation on Governments



values would over time result in a 6.5% reduction in overall tax revenues. Given budget balance requirements, the fiscal hole left by declining office and retail property tax revenues would need to be plugged by raising tax rates or cutting government spending. Both would affect the attractiveness of the city as a place of residence and work. These dynamics risk activating an urban doom loop (Figure 17). With more people being able to separate the location of work and home, the migration elasticity to local tax rates and amenities may now be larger than in the past. Future research should explore these implications and study the role for local and federal policy.

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

Trends in office occupancy have prompted discussion on the merits of conversion of office, either from A-/B/C to A+ office or to alternative use such as multi-family. The former conversion could make sense in light of the flight to quality and the likely dearth of new office construction for years to come. The latter conversion makes sense in light of the lack of (affordable) housing in large cities, but often runs into issues relating to the structural feasibility, zoning restrictions, and return on investment. Older buildings tend to be more amenable to apartment conversion. Whether and how these conversions take place will have an important impact on the future of cities. Given the negative externalities associated with office vacancy, there may be a role for local governments to subsidize the conversion and speed up the transition towards a smaller office stock and larger housing stock.

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Internet Appendix

A Additional Empirical Results

A1 Relationship between NER and Building Age

Table A1 provides detailed regression results of the relationship between building age and NER. We control for month and submarket fixed effects (column 1), as well as tenant fixed effects (column 2), and building fixed effects (column 3). The specification in column 3 with both tenant and building fixed effects identifies the quality gradient from tenants that sign multiple leases within the same building at different points in time (at different building ages), enabling a precise estimation of the association between age and rents. Each year of aging reduces NERs by $0.067 per sf in that specification. A building that is ten years older has 2% lower rents relative to the average rent of $34 per sf. Our key test is how this relationship changes over the pandemic, represented as an interaction term in column 4. We observe that interaction of building age and a post-pandemic indicator variable is negative and significant, indicating that young buildings become even more valuable after the pandemic. This specification compares rent outcomes for leases signed in March 2020 and later, relative to leases signed between January 2018 and February 2020. Column 5 uses log NER and log building age, and shows an additional 2.4% point rent elasticity to age. We observe that this association is largely driven by shifts in major markets (columns 6 and 7), and is particularly large in New York and San Francisco (column 8).

Table A1: Building Quality and Rent

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Building Age (Yrs)	-0.108***	-0.071***	-0.145**	-0.083***		-0.089***	-0.066***	-0.076***
	(0.014)	(0.011)	(0.063)	(0.014)		(0.016)	(0.015)	(0.021)
Building Age × Post Pandemic				-0.063***		-0.022**	-0.019	-0.160***
				(0.013)		(0.010)	(0.012)	(0.024)
Log Building Age					-0.082***			
					(0.006)			
Log Building Age × Post Pandemic					-0.038***			
					(0.007)			
Age × Post × Major Market						-0.052***	-0.028**	
						(0.014)	(0.012)	
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Submarket FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tenant FE	No	Yes	Yes	No	No	No	Yes	Yes
Building FE	No	No	Yes	No	No	No	No	No
Sample	Full	Full	Full	2018–2022	2018–2022	2018–2022	2018–2022	2018–2022 SF+NYC
N	433,491	231,868	217,060	117,429	117,305	117,429	47,365	9,334

standard errors in parentheses.

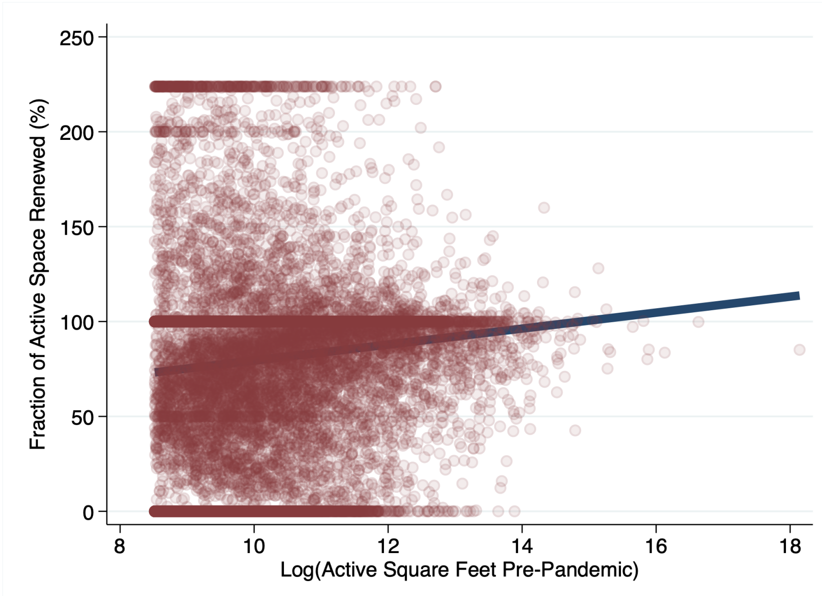
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

A2 Relationship between office demand and tenant size

To illustrate shifting firm space demands during the pandemic across the firm size distribution, Figure A1 plots the relationship between the change in leased space between December 2019 and December 2022 by measuring the change in space at the tenant-level (y-axis) against tenant size, as measured by the log of total sf of active leases before the pandemic (x-axis). We estimate a strongly positive relationship (blue line), which suggests that the decline in tenant space demand is dominated by smaller firms. This is consistent with the idea that small firms are more likely to be financially constrained (Beck, Demirgüç-Kunt and Maksimovic, 2005), and hence more sensitive to the cost of commercial leases and more likely to adopt remote work.

Figure A1: Change in Firm Office Demand and Size



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

A3 Relationship between office demand and remote job postings

As an alternative measure of firms' remote working plans, we use job posting data from Ladders. This data allows us to measure the fraction of a firm's job listings that are for fully-remote positions.[19] We then estimate the relationship between the change in office demand, measured as the percentage change in active lease space in square feet normalized by employment growth since January 2020, and the fraction of job postings that are remote. We merge job postings and tenant data for 135 large tenants.

Table A2 reports the results. The change in office demand is measured over various periods ranging from the last 3 to the last 24 months (relative to the time of data collection in February 2022). We find a significant negative relationship at all horizons. Our results suggest that firms that express a greater remote work preference in job listings have lower demand for office space. A 10% point increase in the share of remote job postings lowers office demand by 3.9–4.9% points. This result is consistent with the idea that durable shifts

[19] The Ladders data contains a flag indicating whether the position is remote or not.

in remote work are changing the demand for office space.

Table A2: 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.

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

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

A4 Relationship between Bank Size and CRE Exposure

In this section, we examine the relationship between bank size and banks' commercial real estate (CRE) exposure using bank call report data. As part of mandatory quarterly reporting, banks' call reports contain bank size, measured as bank book assets, and their exposure to commercial real estate for each quarter end for U.S. commercial banks. We measure CRE loans using the variable "UBPRE629", commercial real estate & related ventures as a percentage of total bank equity, times "UBPR3210", total bank equity capital. UBPRE629 contains the sum of construction and land development loans, nonfarm nonresidential mortgages, unsecured loans to finance commercial real estate, construction and land development, other real estate owned, and investments in unconsolidated subsidiaries and associated companies.

Table A3 reports various categories of bank sizes (column 1), the number of banks in each grouping (column 2), the fraction of aggregate bank assets the group represents (column 3), the asset-weighted average (awa) ratio of CRE loan exposure to bank asset value (column 4), and the fraction of aggregate CRE loans held by banks in that group (column 5). We find that medium and small banks are most exposed to CRE risks, with average exposures of around 20-25%, while the largest banks with over \$250 billion assets have only moderate CRE exposure ($< 5\%$). Nonetheless, the dollar value of their CRE exposure still accounts for 24.3% of all CRE loans.

Table A3: Commercial Real Estate Exposure by Bank Size

(1) Bank Size (\$ bi)	(2) Count	(3) Asset Share (%)	(4) CRE/Asset (%, awa)	(5) Exposure Share (%)
>250	13	55.5	4.5	24.3
100–250	22	15.2	7.9	11.5
50–100	16	4.9	17.7	8.4
25–50	34	5.0	18.7	9.0
10–25	73	5.0	24.4	11.7
2–10	399	7.0	25.5	17.2
0.5–2	1,198	4.8	28.0	13.1
<0.5	3,041	2.6	19.5	4.9

B Working From Home Factor and Office Expected Returns

B1 Model for Expected Returns

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

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

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

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

B2 Constructing a WFH Equity Risk Factor

We form a portfolio (Working From Home factor) that goes long stocks which benefit from remote work and short stocks which suffer from the move to working-from-home. This entails long positions in the technology and health care sectors, and short positions in the transportation, entertainment, and hotel sectors. The WFH factor composition can be found in Table B1. Several variations on the WFH factor construction, such as excluding entertainment stocks or just going long technology stocks and short transportation stocks, give similar results.

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

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

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

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

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:

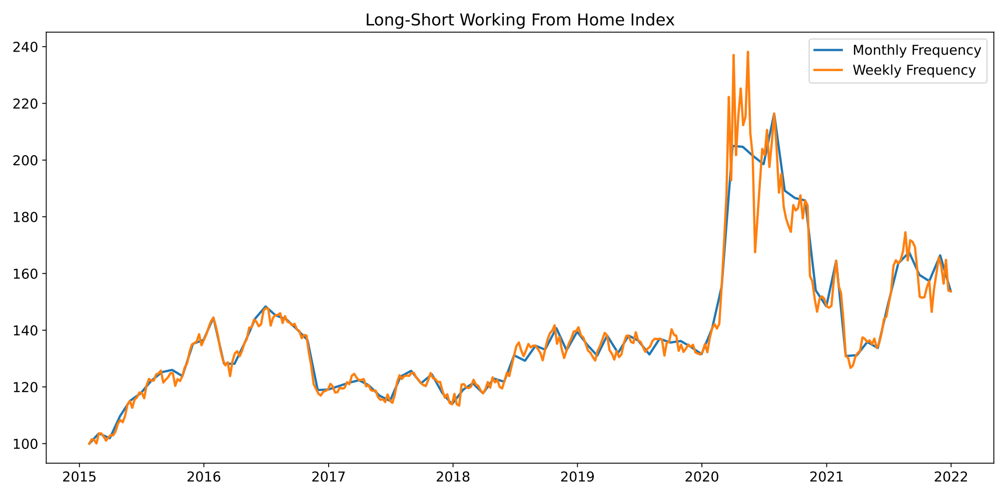
$$R_t = R_{l,t} - R_{s,t}$$

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 at the end of December 2014 since the composition of the WFH index is relatively stable after that date. Prior to 2015, many of the companies in the long or short leg were not trading, such as Zoom. Several perturbations on the WFH index construction deliver similar results. Figure B1 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 B1: Working From Home Risk Factor



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

Table B1: Composition of WFH Index

Panel A: Long Positions

Ticker	Name	Leg	Sector
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
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
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
DOCU	Docusign	Long	Online Document Mgmt
BOX	Box Inc	Long	Online Document Mgmt
UPLD	Upland Software Inc	Long	Online Document Mgmt
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
PTON	Peloton Interactive Inc	Long	Virtual Healthcare
TDOC	Teladoc Health Inc	Long	Virtual Healthcare

Panel B: Short Positions

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
HLT	Hilton Worldwide Holdings In	Short	Hotels
MAR	Marriott International	Short	Hotels
H	Hyatt Hotels Corp	Short	Hotels
IHG	Intercontinental Hotels	Short	Hotels
DAL	Delta Air Lines Inc	Short	Transportation
UAL	United Airlines Holdings Inc	Short	Transportation
AAL	American Airlines Group Inc	Short	Transportation
LUV	Southwest Airlines Co	Short	Transportation
CCL	Carnival Corp	Short	Transportation
NCLH	Norwegian Cruise Line Holdin	Short	Transportation
UNP	Union Pacific Corp	Short	Transportation

B3 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:

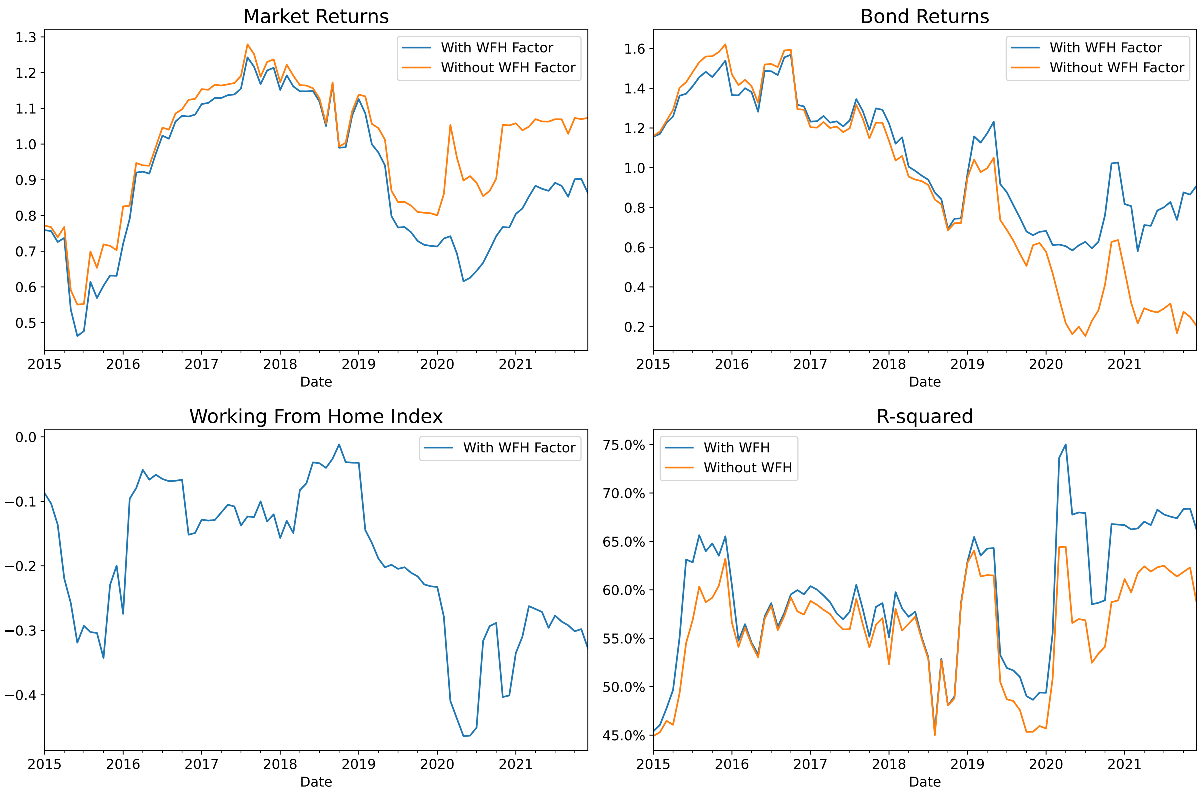
$$r^o_{t+1} - r^f_t = \alpha + \beta^m_t (r^m_{t+1} - r^f_t) + \beta^b_t (r^b_{t+1} - r^f_t) + \beta^{wfh}_t r^{wfh}_{t+1} + e_{t+1} \quad (8)$$

Figure B2 shows the estimated betas for office REITS. The patterns in the stock and bond betas of office REITS in the three-factor model (blue line) are similar to those in the two-factor model without the WFH factor (orange line) before the pandemic. However, omission of the WFH factor leads one to overstate the stock market beta during the pandemic (top left panel). The reverse is true for the bond beta in the top right panel.

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

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

Figure B2: Risk Exposures of Office REITs During Covid with WFH



B4 WFH Risk Price

We estimate the market prices of risk on the WFH factor, λ^{wfh}, using the cross-section of 22 individual office REITs listed in Table B2.

Table B2: List of Office REITS

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

We use a two-stage Fama-MacBeth procedure. In the first stage using the time-series, we estimate 36-month rolling-window regressions of each REIT's return on the three factor returns; i.e., we estimate equation (8) for each REIT separately. In the second cross-sectional step, we regress the realized return each month on the betas for that month. The market price of risk estimates are the average of the monthly slope estimates of the second step. We use only the months prior to the onset of the pandemic (December 2014–December 2019) when computing this average. Since the WFH index saw unusually high realizations during the pandemic, inclusion of the pandemic months would lead one to confuse realized with expected returns, while in fact the two are negatively correlated. We obtain $\hat{\lambda}^{wfh} = -7.0\%$ annualized (t-stat is -0.52 but the sample is short to reliably estimate this coefficient).[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 coronavirus pandemic surges. Conversely, negative returns to WFH, such as Nov 8, 2020 when the vaccine discovery news first broke, are good states of the world.

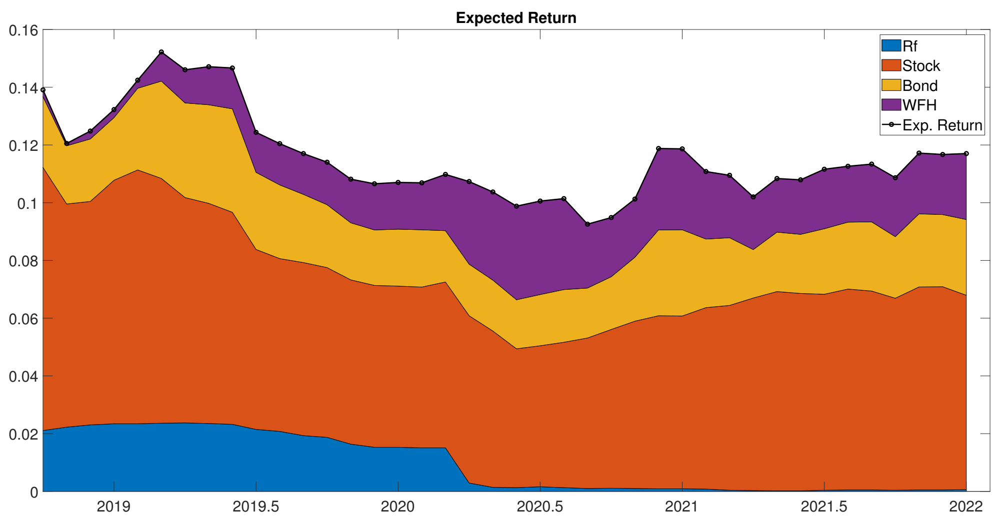
B5 Expected Returns

For the risk prices on stocks and bond, we use the sample average of the estimated risk premia in the post-1994 period: $\lambda^m = 7.81\%$ and $\lambda^b = 2.91\%$. For the WFH risk price we use $\lambda^{wfh} = -7.0\%$, as estimated above. We combine the three time-varying betas from Figure B2 with the market price of risk estimates to form the expected return on office REITs as per equation (7). Figure B3 plots the resulting expected return. While the contribution from stocks and bond market risk shrinks over the course of the pandemic, by virtue of the declining stock and bond betas, the contribution from the WFH risk exposure (in purple) is substantial. WFH risk contributes about 2–3% points to the expected return on office during the pandemic.

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

[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 B3: Expected Return of Office REITs During Covid



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

C1 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 sf on existing leases, and R_{t+1}^m is the market net effective rent per sf on newly executed leases. R_t^O is a geometrically-decaying weighted average of all past market rents,

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

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

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

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

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

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

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

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

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

We 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 $R_{t+1}(\hat{Q}^O_t, \hat{R}^O_t, z')$:

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

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

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

The expected present discounted value (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 of revenues can be written as:

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

which solves the following Bellman equation:

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

Finally, we get V_t^R by

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

C2 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,

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

We define scaled costs as:

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

Therefore, we have:

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

where

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

The expected PDV of costs is written as:

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

The scaled version is:

$$\hat{V}^C_t = \frac{V^C_t}{\overline{Q}_t R^m_t},$$

which solves the Bellman equation

$$\hat{V}^C_t(\hat{Q}^O_t, z) = \sum_{z'} \pi(z'|z) M(z'|z) \left\{ \widehat{Cost}_{t+1}(\hat{Q}^O_t, z') + (1+\eta(z')(1+\epsilon(z'))\hat{V}^C_{t+1}(\hat{Q}^O_{t+1}, z') \right\}.$$

Finally, we get V^C_t by

$$V^C_t = \hat{V}^C_t(\hat{Q}^O_t, z)\overline{Q}_t R^m_t.$$

C3 Closed-form solutions

First, we define matrix notations for parameters:

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

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

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

$$S^O_{4x4} = \Big[s^O_{4x1},\, s^O_{4x1},\, s^O_{4x1},\, s^O_{4x1}\Big]'$$

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

C3.1 Cost Valuation

We express $\widehat{Cost}_{t+1}(\hat{Q}^O_t, z')$ as a linear function of $\hat{Q}^O_t$:

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

where

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

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

Next, 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:

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

As a result, 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:

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

C3.2 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 is independent to $\hat{Q}^O_t$ or $\hat{R}^O_t$:

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

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 (9) 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 $\hat{R}_t^O$:

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

Thus, we can conclude:

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

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

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

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

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

where

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

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

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

By comparing terms, we can conclude that

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

and solve the intercept term in the linear system:

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

C4 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 Calibration Algorithm

The following describes the steps in the calibration algorithm for the universe of NYC office buildings (All NYC) and the subset of A+ buildings (NYC A+). We set the depreciation to 2.56% in both calibrations, a realistic annual depreciation rate for commercial office, consistent to the tax depreciation of commercial properties of 39 years. The calibration for All NYC takes the persistence parameter of the WFH state, p, as given. This parameter is pinned down from the A+ calibration. Conversely, the calibration for NYC A+ takes the parameter $\Delta\eta$ as given. This parameter is pinned down from the All NYC calibration. Hence, the two calibrations are interdependent: they solve a fixed-point problem.

D1 All NYC, given p

1. Keep only office buildings and exclude subleases in the CompStak data set of leases for NYC.

2. Calculate the average lease term for all leases in NYC. Set χ equal to the reciprocal.

3. Estimate ε from data:

   (a) To estimate $\varepsilon(E)$ and $\varepsilon(R)$, first calculate NER series for each month controlling for submarket, tenant industry, leasing type, and building class FEs, and take the 6-month moving average. Use data from January 2000 (start of CompStak) until December 2019.

   (b) If more than 6 months of the 1-year window falls in recession, then the year is considered to be a recession; otherwise it is considered to be an expansion. Use the leasing cycle definition instead of the business cycle.

   (c) Compute the annual growth rate of the six-month moving average, and take the average separately for expansions and recessions.

   (d) Estimate $\epsilon(WFHR)$ as the realized NER growth between December 2019 and December 2020, and $\epsilon(WFHE)$ as the annualized realized rent growth between December 2020 and December 2022.

   (e) Since the values for $\varepsilon(E)$ and $\varepsilon(R)$ are determined based on the leasing cycle rather than the business cycle, adjust all four $\varepsilon(z)$ parameters by a constant so that the mean of simulated rent growth from 2000 to 2019 matches the sample mean.

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

   (a) Compute the growth rate in floor space in year t as the newly constructed office square feet in year t relative to the total square feet of office space built before year t. This uses the full history of construction years in our CompStak dataset.

   (b) Year t is a recession when more than six months of that year is in recession.

   (c) We take the average the construction growth rate across expansions and recessions.

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

5. Set $\eta(WFHE) = \eta(E) + \Delta\eta$ and $\eta(WFHR) = \eta(R) + \Delta\eta$. Find the $\Delta\eta$ such that the long-run growth rate of potential rent in the All NYC is zero:

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

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

6. Estimate the four parameters $\{s^O(E), s^O(R), s^V(E), s^V(R)\}$ to match the following four moments in quarterly Manhattan office occupancy rate data for from 1987.Q1 to 2020.Q1:

   (a) empirical mean

   (b) empirical standard deviation

   (c) empirical min - 0.5%

   (d) empirical max + 0.5%

7. Assume that the four parameters $\{s^O(WFHE), s^O(WFHR), s^V(WFHE), s^V(WFHR)\}$ are shifted by a common factor δ relative to their no-WFH counterparts: $s^{\{V,O\}}(WFH) = \delta \cdot s^{\{V,O\}}(no - WFH)$. Estimate the parameter δ to best fit the dynamics of the office occupancy rate in the nine quarters from 2020.Q2–2022.Q2. These dynamics are given by the model:

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

   Simulate the law of motion for occupancy from 1930 until 2019, under the observed sequence of expansions and recessions, to arrive at the initial condition for $\hat{Q}^O$ in 2020.Q1. Next, we simulate the occupancy process forward for the next 12 quarters assuming that the first four quarters are WFH-R observations and the last eight are WFH-E. We find the δ that minimizes the distance between the model and the data.

D2 NYC A+, given $\Delta\eta$

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

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

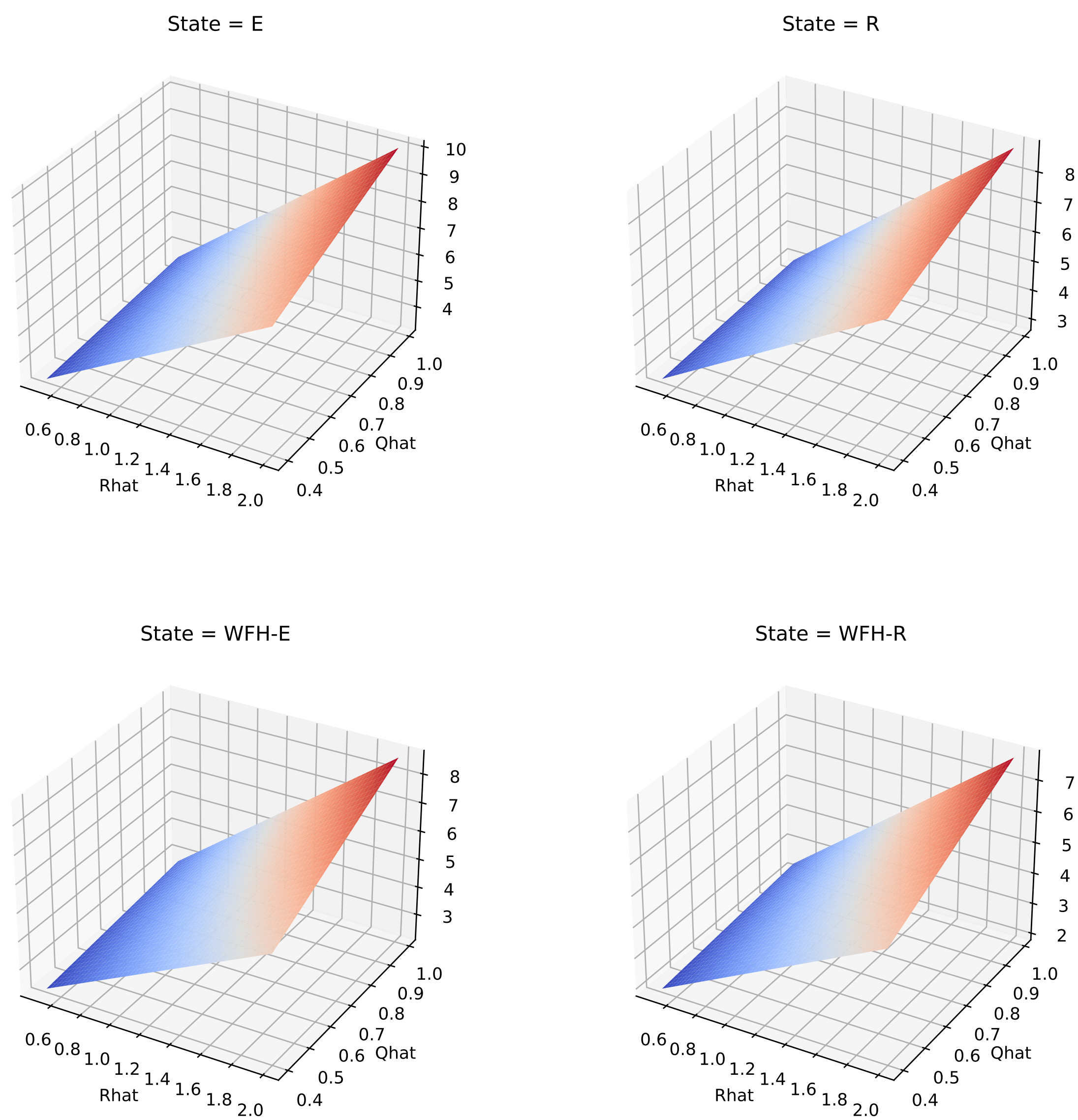
5. The NYC A+ calibration takes $\Delta\eta$ from the All NYC calibration.

6. We use data from NAREIT on office sector occupancy from 2000.Q1 to 2020.Q1 to calibrate $\{s^O(E), s^O(R), s^V(E), s^V(R)\}$. We target a minimum occupancy rate equal to the empirical minimum—6.5%—because the A+ occupancy data is missing the 1990s, the worst historical period for office occupancy.

8. Given all other parameters, find p to match the observed realized return on NYC-centric office REITS between December 31, 2019 and December 31, 2020, after adjusting for leverage. See the discussion in Section 3.4.

Figure D1 shows the valuation ratio for office $\widehat{V}$ conditional on expansion, recession, WFH-expansion and WFH-recession for the All NYC calibration. The x-axis plots the grid for $\widehat{Q}^O$ and the y-axis shows the grid for $\widehat{R}^O$. Office valuation ratios are increasing in both occupancy $\widehat{Q}^O$ and rent premium $\widehat{R}^O$.

Figure D1: $\hat{V}$ for All NYC Market by States



E Results for NYC A+ Market

Table E1 shows the calibration of the cash-flow parameters for the A+ market segment, following the algorithm outlined in appendix D. Naturally, the state transition and SDF matrices are the same for all properties.

Table E1: Calibration for NYC A+

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0655	-0.1448	0.0367	-0.0900
Supply growth	η	-0.0148	-0.0077	-0.0261	-0.0190
Lease renewal share	s^O	0.8509	0.5708	0.6692	0.4489
New leasing share	s^V	0.1195	0.1929	0.0940	0.1517

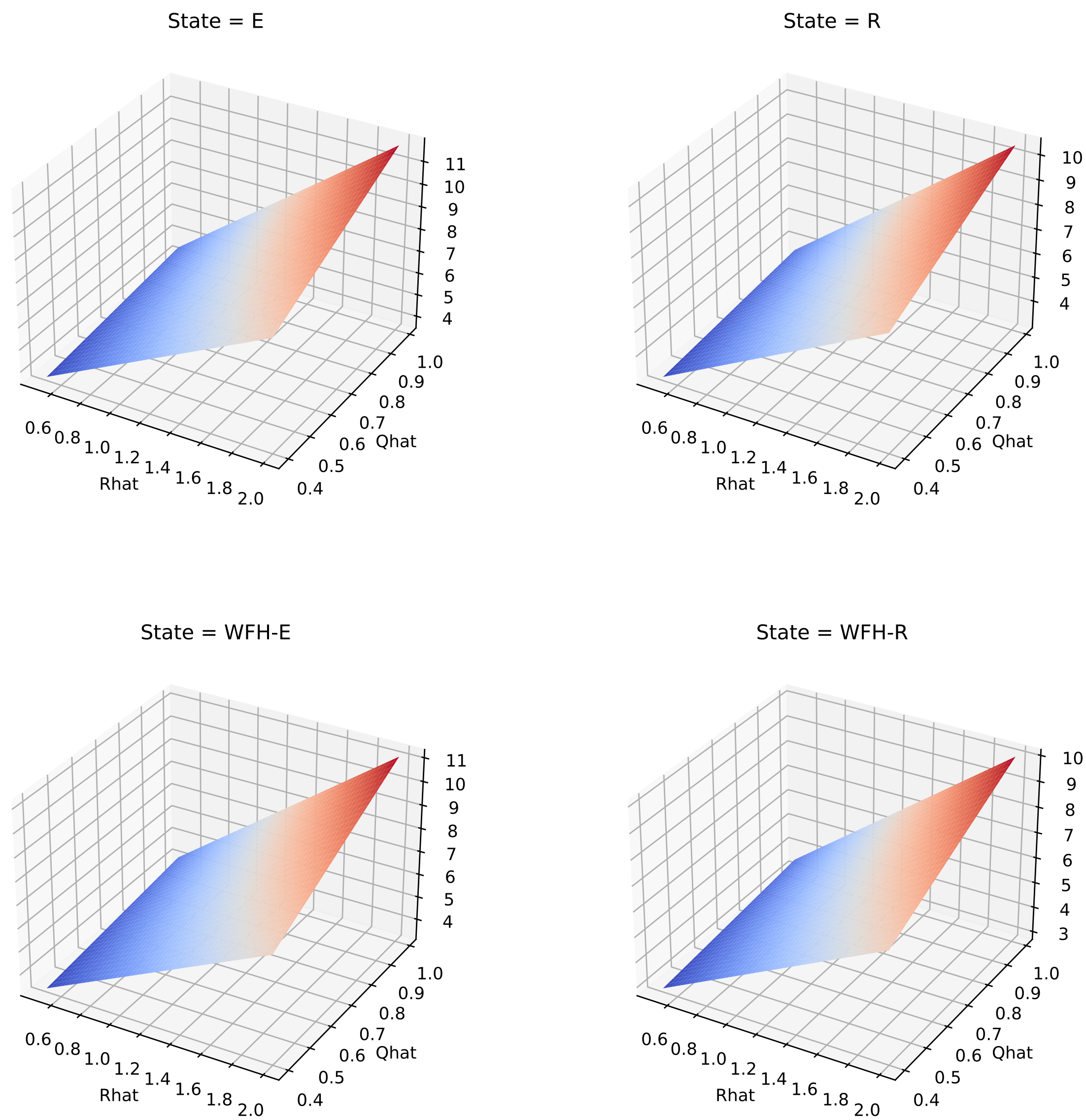
Table E2 shows the model solution for the A+ calibration. The model delivers a lower cap rate for A+ NYC office, due to the lower riskiness of A+ cash flows. Class A+ has lower vacancy levels than the market as a whole, on average as well as in the WFH states.

Appendix Figure E1 shows the valuation ratio $\widehat{V}$ in each state as a function of occupancy and rent state variables.

Table E2: Model Solution for NYC A+ Calibration

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.0632	0.0584	0.0831	0.0607	0.0780
Office $\mathbb{E}[Ret] - 1$	0.0670	0.0581	0.1482	0.0456	0.1246
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0521	0.0497	0.1014	0.0372	0.0779
$\mathbb{E}\left[g_t\right]$	0.0028	-0.0153	0.1424	-0.0238	0.0688
Vacancy rate $= 1 - \widehat{Q}^O$	0.1175	0.0844	0.1248	0.1412	0.1699
$\widehat{\text{Rev}}$	0.7914	0.7848	0.9366	0.7553	0.8364
$\widehat{\text{Cost}}$	0.4180	0.4282	0.4182	0.4098	0.4031
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.3734	0.3566	0.5184	0.3455	0.4334
$\widehat{V}^R$	10.3777	10.7885	9.7849	10.2875	9.3129
$\widehat{V}^C$	4.5387	4.7747	3.6606	4.6380	3.8081
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	5.8390	6.0139	6.1242	5.6496	5.5048

Figure E1: $\hat{V}$ for NYC A+ Market by States



F Calibration to Other Markets

We repeat the calibration procedure discussed in the main text and in Appendix D for San Francisco and Charlotte. We use CompStak data to measure market rent growth, ε, before and during the pandemic. We also use CompStak data to measure pre-pandemic office construction rates (η is the construction minus the depreciation rate). Like in the NYC calibration, net supply growth rates during the pandemic (WFHR and WFHE) are set equal to their pre-pandemic counterparts (R and E) minus an adjustment factor (the same as NYC one). Due to the incomplete building coverage in CompStak, estimation of η for San Francisco and Charlotte starts in 1980. We use contractual occupancy rate data from Cushman and Wakefield to calibrate s^O and s^V before and during the pandemic. We leave the office depreciation rate and the operational cost parameters the same as in the NYC calibration. Naturally, we assume that the dynamics of the aggregate state variable $\pi(z', z)$ are common across markets, as well as the market prices of risk $M(z', z)$.

Table F1 shows the calibrated parameters for San Francisco and F2 shows those for Charlotte. Table F3 and F4 show the main moments for San Francisco and Charlotte, respectively. The SF office market is riskier than the NYC market, featuring a rent cycle of greater amplitude which translates into a higher risk premium and cap rate. The opposite is true for Charlotte. Figure F1 plots fan charts for occupancy rates, revenues, NOI and cap rates for San Francisco and Charlotte.

Table F1: Calibration for San Francisco

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.1143	-0.1610	-0.0596	-0.1537
Supply growth	η	-0.0183	-0.0106	-0.0296	-0.0218
Lease renewal share	s^O	0.8540	0.6738	0.4244	0.3348
New leasing share	s^V	0.2372	0.1948	0.1179	0.0968

Table F2: Calibration for Charlotte

Variable	Symbol	E	R	WFH-E	WFH-R
Market NER growth	ϵ	0.0870	-0.1334	0.0101	-0.0702
Supply growth	η	0.0017	0.0208	-0.0096	0.0095
Lease renewal share	s^O	0.9048	0.8747	0.6398	0.6185
New leasing share	s^V	0.2900	0.1156	0.2050	0.0817

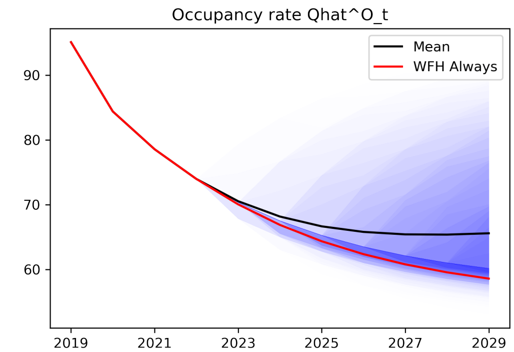
Table F3: Model Solution for San Francisco Calibration

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.1076	0.0831	0.1235	0.1232	0.1446
Office $\mathbb{E}[Ret] - 1$	0.0934	0.0921	0.2151	0.0575	0.1345
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0785	0.0837	0.1684	0.0491	0.0878
$\mathbb{E}[g_t]$	-0.0231	-0.0029	0.1584	-0.0820	-0.0513
Vacancy rate $= 1 - \widehat{Q}^O$	0.2490	0.1085	0.1662	0.3879	0.4205
$\widehat{\text{Rev}}$	0.7727	0.7894	0.9219	0.7223	0.7584
$\widehat{\text{Cost}}$	0.3976	0.4370	0.4221	0.3583	0.3498
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.3751	0.3524	0.4998	0.3640	0.4087
$\widehat{V}^R$	6.7643	8.3196	6.9993	5.3865	4.8673
$\widehat{V}^C$	3.1917	4.1211	3.0039	2.4464	2.0529
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	3.5727	4.1985	3.9954	2.9402	2.8144

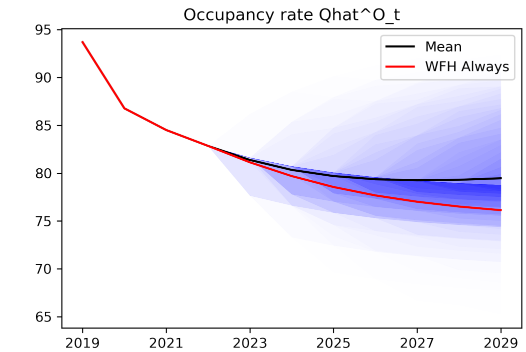
Table F4: Model Solution for Charlotte Calibration

Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.0569	0.0500	0.0742	0.0583	0.0679
Office $\mathbb{E}[Ret] - 1$	0.0850	0.0786	0.2032	0.0521	0.1427
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0701	0.0702	0.1565	0.0437	0.0960
$\mathbb{E}[g_t]$	0.0233	0.0217	0.1460	-0.0060	0.0337
Vacancy rate $= 1 - \widehat{Q}^O$	0.1614	0.0914	0.1444	0.2183	0.2774
$\widehat{\text{Rev}}$	0.7932	0.8053	0.9126	0.7593	0.7573
$\widehat{\text{Cost}}$	0.4196	0.4403	0.4270	0.4019	0.3871
$\widehat{\text{NOI}} = \widehat{\text{Rev}} - \widehat{\text{Cost}}$	0.3735	0.3650	0.4856	0.3574	0.3701
$\widehat{V}^R$	12.7811	14.1073	11.7336	12.0423	10.4920
$\widehat{V}^C$	6.1817	6.8369	5.2303	5.9188	5.0485
$\widehat{V} = \widehat{V}^R - \widehat{V}^C$	6.5994	7.2703	6.5032	6.1235	5.4435

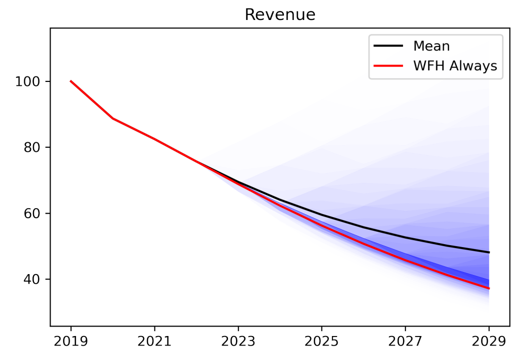
Figure F1: Fan Charts for San Francisco and Charlotte



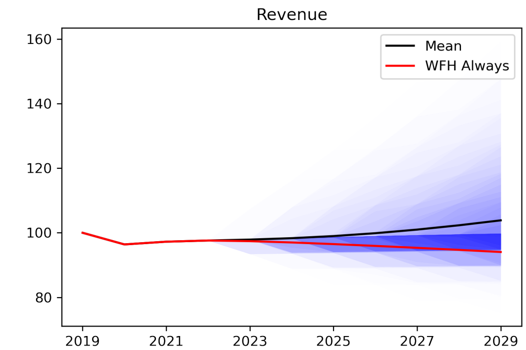
(a) San Francisco: Occupancy



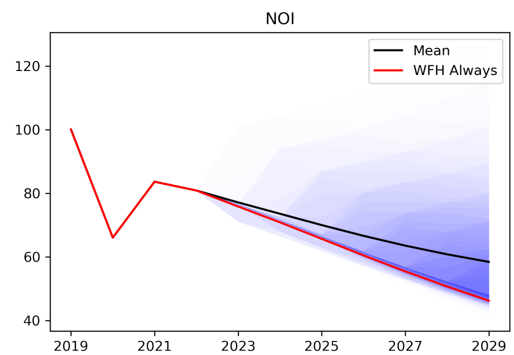
(b) Charlotte: Occupancy



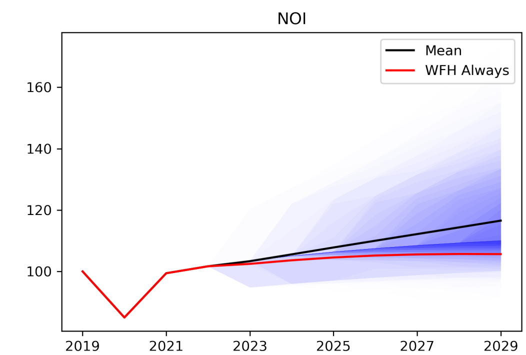
(c) San Francisco: Revenue



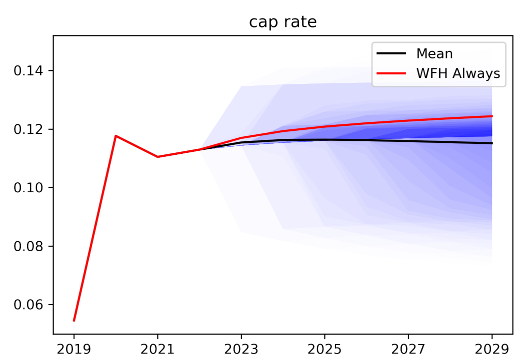
(d) Charlotte: Revenue

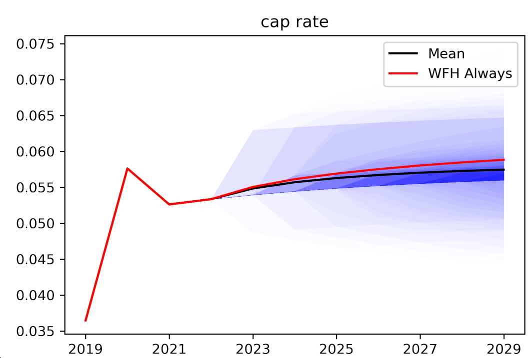


(e) San Francisco: NOI



(f) Charlotte: NOI





(g) San Francisco: Cap Rate

(h) Charlotte: Cap Rate

G Additional Model Results

G1 Term Structure of Valuations

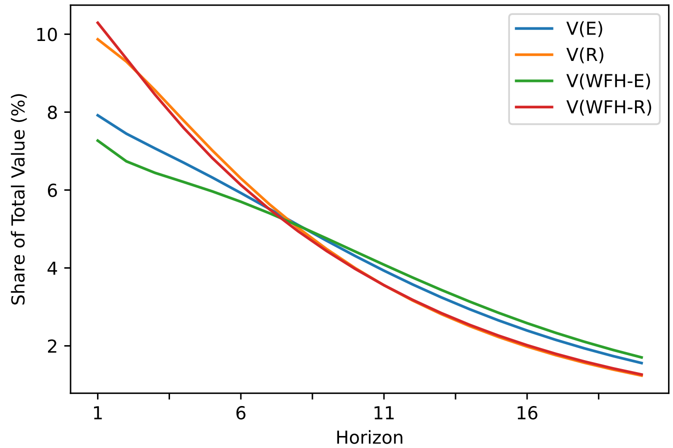
We can decompose the (change in) office value into the contribution from each of the future cash flows. Appendix C4 explains the procedure. Figure G1 plots the share of the total value of office that comes from each of the first 20 years of cash flows. The lines are downward sloping as cash flows in the near term are more valuable than cash flows farther in the future due to discounting. Each line refers to a different current state for the economy. Interestingly, in expansions (such as 2019) the contribution of the nearest-term cash flows is much smaller than in the WFH-R state (such as 2020). For the share of short-term in total cash flows to rise (in present-value) between 2019 and 2020, the value of the cash flows in the farther future must falls by more than in the near future. This occurs because rents (and NOI) in the short-term are largely locked in given the long-term nature of leases. Investors would be willing to pay a premium for buildings that have a lot of long-term pre-pandemic leases in place.

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

G2 Sensitivity to WFH-R Rent Growth

Figure G2 shows the office valuation for NYC under an alternative assumption on NER growth in the WFH-R state, namely that it equals the NER growth in a regular recession state R. The impact on the model prediction is minimal.

Figure G1: Decomposing Office Values by Horizon



G3 Shutting Down WFH Risk Channel

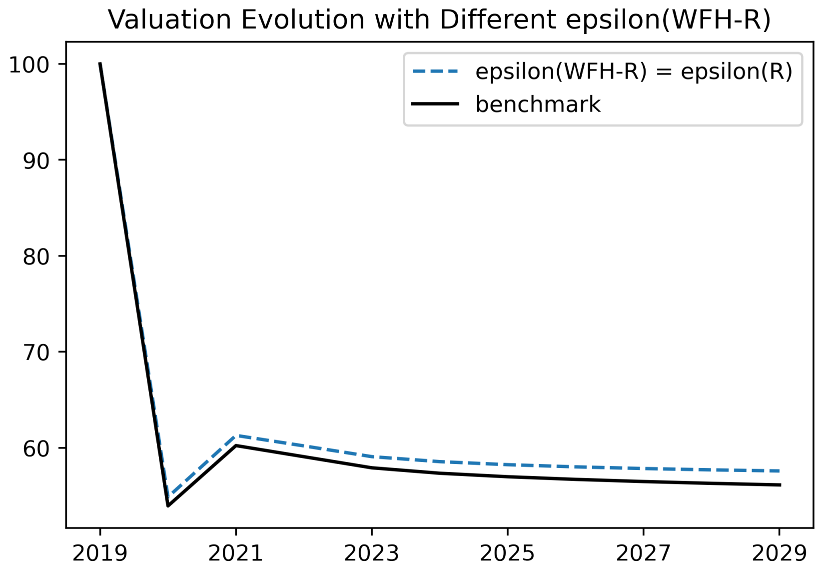
Figure G3 shows the valuation impact in a model where there is no priced WFH risk. We compute this model by setting the component of the SDF that encodes WFH risk equal to the identity matrix: $M^{WFH} = 1$. The impact on the value decline of NYC office is -42.4% in 2020 and -39.4% in 2029, relative to pre-pandemic levels. The corresponding numbers in the benchmark model are -46.1% and -43.9%.

G4 Robustness Tests for San Francisco

Figure G4 performs four sensitivity analyses for San Francisco changing (i) rent growth in the WFH-E state, a state in which the model spends a lot of time conditional on making the transition to a WFH state (panel a), (ii), the gap between net supply growth in the WFH relative to the no-WFH states (panel b), (iii), the persistence of remote work p, and (iv), introducing a floor for office values set at 30% of pre-pandemic valuations, as a simple way to model additional optionality from adaptive reuse not already captured by the net supply parameter η.[22]

[22]This specification is intended to capture the redeployability option, as in Kim and Kung (2017) and Benmelech, Garmaise and Moskowitz (2005), as office buildings may ultimately be converted to other uses. We use 30% as a rough benchmark for the option value to covert to other uses. A fuller consideration of this option—which will be affected by interest rates, costs of conversion, and demand for other uses among other factors—is

Figure G2: Setting $\epsilon(WFH - R) = \epsilon(R)$



outside of the scope of our analysis, which is focused on valuing cash flows resulting from buildings operated as commercial office buildings.

Figure G3: Shutting Down the Risk Channel

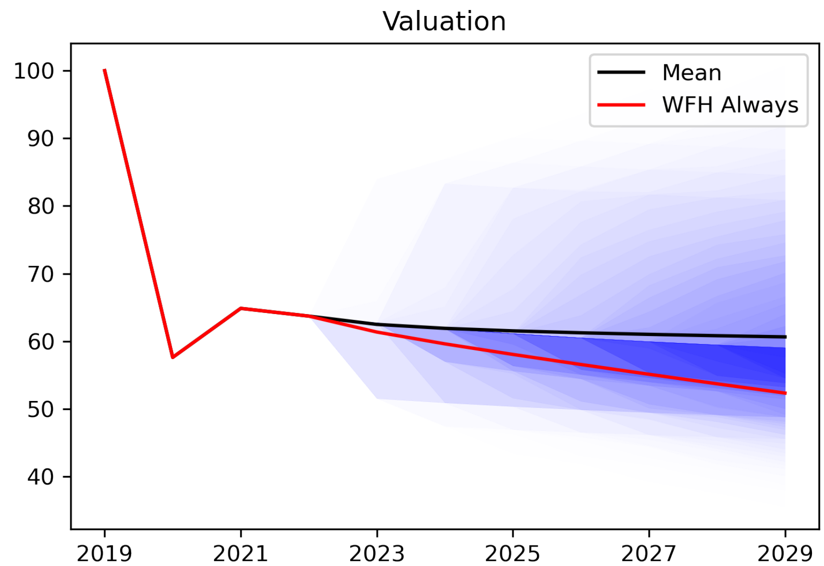
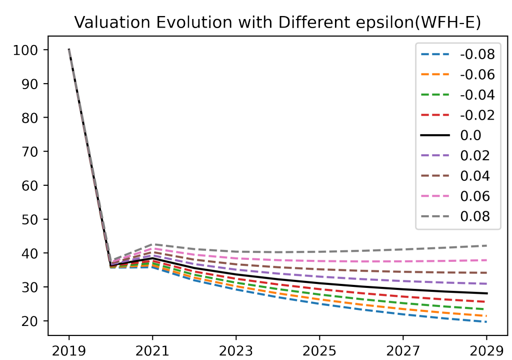
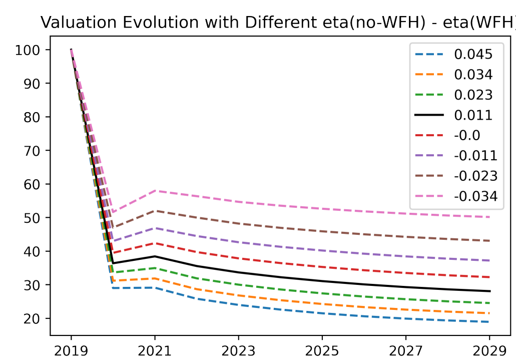


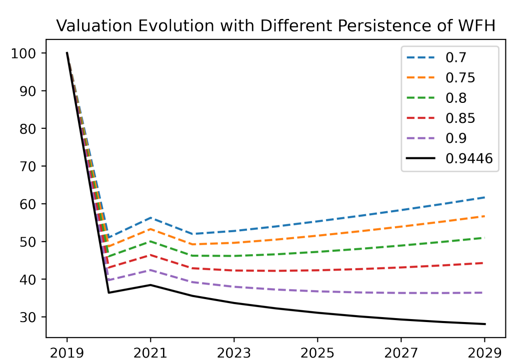
Figure G4: Robustness Tests for San Francisco



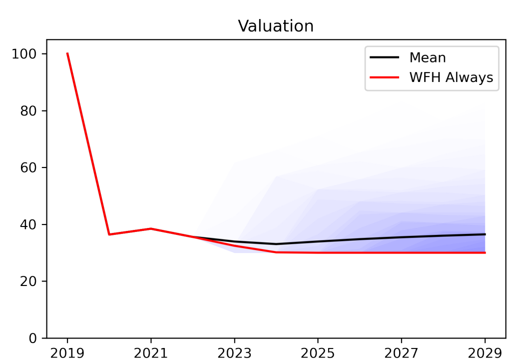
(a) Different $\epsilon(WFH - E)$



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



(c) Different Persistence of WFH



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