

Appendix for Online Publication

Work From Home and the Office Real Estate Apocalypse

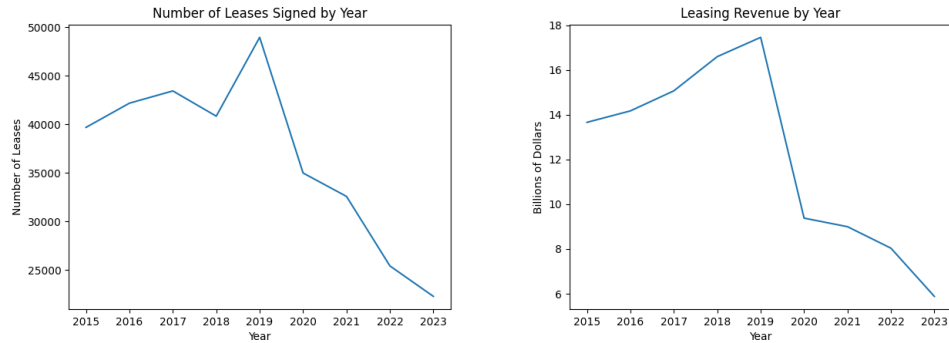
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ADDITIONAL EMPIRICAL RESULTS

A1. Summary Statistics on Leasing

This section provides summary statistics for the CompStak data we use in this paper: We have 105 markets, 106,624 unique buildings, 623,030 leases, and 360,684 unique tenants in our entire sample. Figure A1 plots the number of newly signed leases per year between 2015 and 2023 in the left panel, and the dollar value of those leases (in December 2022 dollars, right).

Figure A1. : New Leasing Activities (2015-2023)



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

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

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

Extension and Expansion leases are categorized in Cushman & Wakefield data. In our CompStak data set, we include these under renewal leases.

Table A1—: Manhattan Leasing Coverage Ratio

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

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

A2. Evolution of Prices and Quantities of Newly-Signed Leases

NEW LEASE RENTS

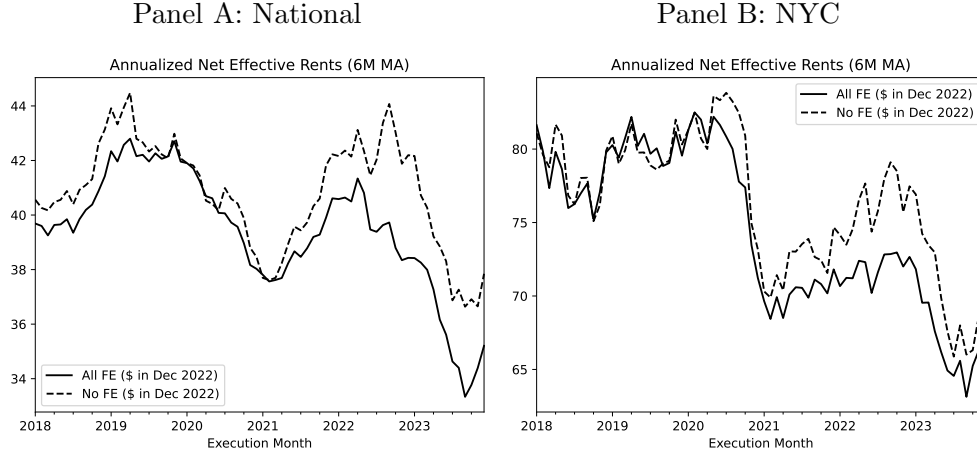
We study the dynamics of net effective rents (NER) on newly-signed leases. Figure A2 shows the square-foot weighted average NER on new leases, expressed in December 2022 dollars. Panel A shows results for the U.S. and Panel B subsets on NYC. Nationally, the NER fell by 8.59% in 2020. Starting in early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

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

NEW LEASE QUANTITIES

Figure A3 investigates the effect of changes in office demand on the volume of new lease agreements. To do so, we aggregate the total number of new commercial

Figure A2. : Net Effective Rent on New Leases



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

office leases signed in the CompStak data. We observe a large decrease in the quantity of new leases signed, sometimes called absorption. Nationally (In NYC), the volume of newly signed leases fell from 414.09 (39.99) million square feet (sf) per year in the last six months of 2019 to 150.46 (20.72) million sf per year in the last six months of 2023. The graph suggests a large reduction in office demand from tenants who are actively making space decisions.

NEW LEASE DURATIONS

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

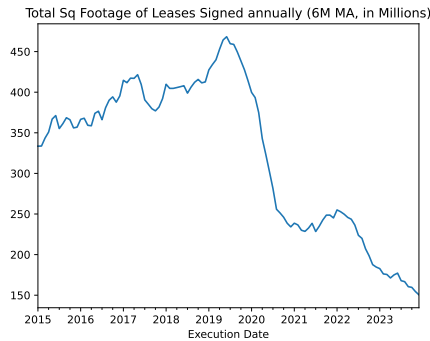
The shortening of lease duration suggests important shifts in the commercial office market, even conditional on lease renewal. As a result, the coming years 2024–2026 will feature even larger than expected lease expiration from two channels: the pre-scheduled expiration of long-term leases signed before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

A3. Flight To Quality

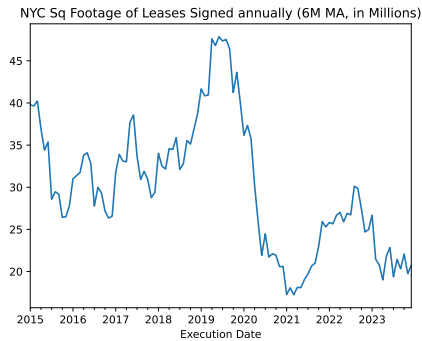
We label the highest quality buildings as class A+ properties, defined based on rent levels and age. Specifically, we isolate leases that are either (1) in the

Figure A3. : Quantity of New Leases Signed

Panel A: National



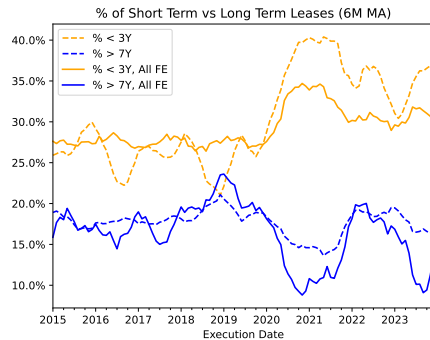
Panel B: NYC



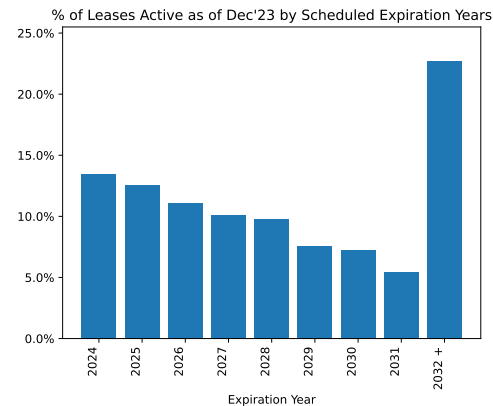
Notes: The graph shows the quantity of leases signed in square feet over time. Data are sourced from CompStak.

Figure A4. : Lease Durations and Current Expiration Schedule

Panel A: Lease Duration Changes



Panel B: 2023 Expiration Schedule



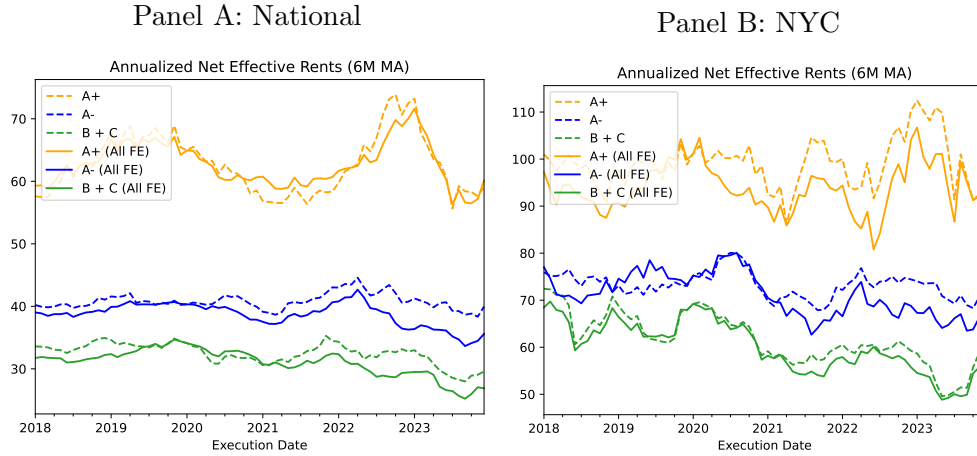
Notes: Panel A shows the share of short-term (less than 3 year duration, in orange) and the share of long-term (more than 7 year duration, in blue) leases over time. Dashed lines denote raw data while the solid lines remove state, major/non-major market, industry, and renewal fixed effects. Panel B shows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

top ten percent of the NER distribution in each quarter and submarket among all properties that are ranked as Class A by CompStak or (2) from buildings younger than five years. For the first “high rent” criteria, we categorize a building that has such a lease as A+ and assume that the A+ status remains for five years, unless another top-10% lease is signed in that building at which point the five-

year clock resets. We pause new high-rent-criteria-based entry into the A+ group after December 2019 to avoid self-selection in the “flight-to-quality” effect. By this definition, 26.9% of square feet and 34.4% of lease revenue is in A+ office buildings in New York City. The remaining buildings (“others”) are classes “A-” (A without A+), B, and C.

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

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



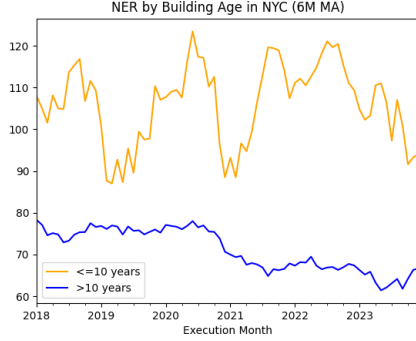
Notes: The figure shows annualized net effective rents on newly-signed leases for all markets (Panel A) and NYC (Panel B). Rents are shown rents by building class: A+ (in orange), A- (in blue), B+C (in green). Dashed lines denote raw data while solid lines remove tenant industry, renewal, and state plus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

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

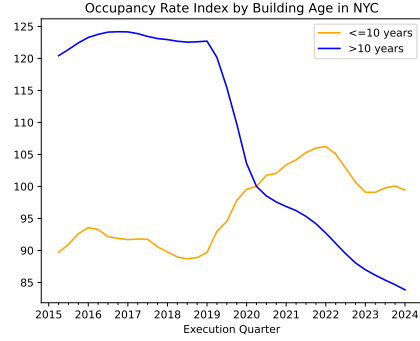
Panel B of Figure A6 shows changes in occupancy, which is the other main driver of revenue. The graph breaks out trends in occupancy across buildings of different ages. Occupancy rates are scaled relative to their December 2019 levels. The clearest expression of quality differentiation reveals itself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

Figure A6. : Flight to Quality Defined by Building Age

Panel A: NER in NYC



Panel B: Occupancy in NYC



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

Table A2 provides detailed regression results of the relationship between building age and NER. We control for month and submarket fixed effects (Column 1), and additionally for tenant fixed effects (Column 2). The specification in column 2 identifies the quality gradient from tenants that sign multiple leases, enabling a precise estimation of the association between age and rents. Each year of aging reduces NERs by \$0.083 per sf in that specification. A building that is ten years older has 2.4% lower rents relative to the average rent of \$34.6 per sf.

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

A4. Measures of Physical Office Attendance

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

Table A2—: Building Quality and Rent

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

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

KASTLE SYSTEMS

Kastle Systems provides the Kastle Back-to-Work Barometer, which has become a widely cited measure of office occupancy during and after the COVID-19 pandemic. The data are drawn from proprietary access control software, with activity data from keycard, fob, and app usage across the buildings that Kastle secures. The Kastle data covers 2,600 buildings and 41,000 businesses across 47 states. In Manhattan, the data is drawn from 200 buildings and 70,000 cardholders. Kastle reports that nearly two-thirds of its sample comes from Class A commercial buildings, but it also includes a range of other buildings to reflect the city’s entire office real estate market. This fraction is similar to the composition of Class A buildings in our CompStak dataset, suggesting representativeness along this dimension.

PLACER.AI

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

XYSENSE

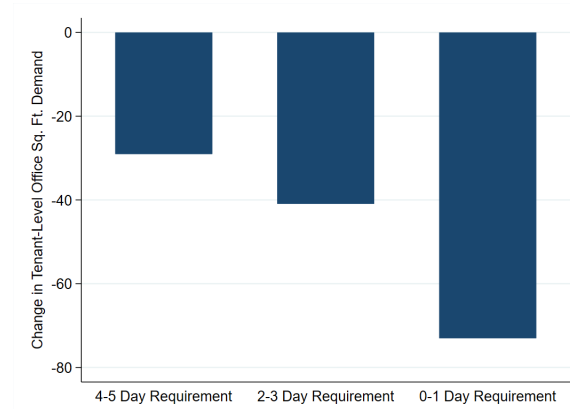
XYsense uses remote sensing technology to create a Workplace Utilization Index. These are based on sensors installed in office spaces to detect occupancy and movement patterns. Though specific coverage details are not publicly available, XYsense markets its solutions to a wide range of companies across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

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

A5. *Relationship between office demand and remote work*

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

Figure A7. : Firm Work Mode and Weighted Office Demand



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

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

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

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

We then estimate the relationship between the change in office demand, measured as the percentage change in active lease space in square feet normalized by employment growth since January 2020, and the fraction of job postings that are remote. We merge job postings and tenant data for 135 large tenants. Table A4 reports the results. The change in office demand is measured over various

Table A3—: Remote Work and Office Space Demand/Rent

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

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

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

Table A4—: Remote Listings and Office Demand

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

t statistics in parentheses.

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

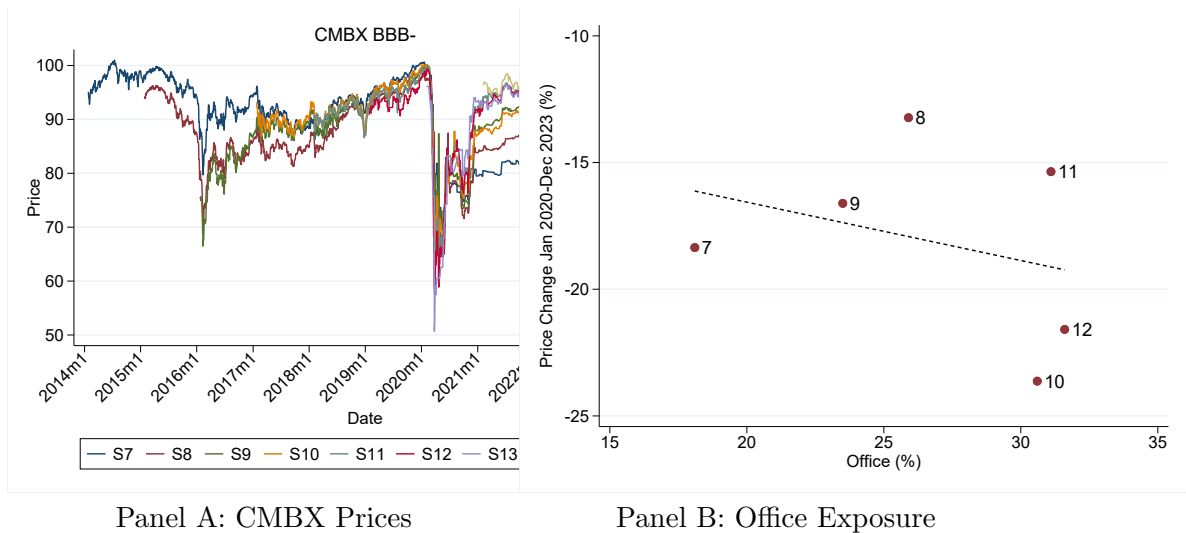
Notes: The dependent variable, Δ Space, is constructed from CompStak and defined as the square feet (sf) of leases executed post-pandemic minus the positive part of the difference between sf of leases expired post-pandemic and sf of leases commenced post-pandemic, and normalized by pre-pandemic active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

A6. Evidence from Public Debt Markets

Declining office valuations could be substantial enough to inflict losses on debtholders. Evidence from public debt markets is directionally consistent with this possibility. Figure A8 plots the time series of prices of CMBX tranches with credit rating BBB- of different vintages (Bloomberg, 2024). Every six months, a new vintage of CMBX tranches is issued, indicated by a sequential number (we plot series S7–S15). Each BBB- CMBX tranche represents a pool of 25 BBB- tranches of the 25 largest CMBS deals issued in that six-month period. The collateral pool of each CMBS deal consists of a mix of office, retail, industrial, apartment, and hotel properties. The share of the collateral that consists of office-backed mortgages varies across the pre-2020 vintages (S7–S12). It is higher for series S10–12 than for series S7–9. Panel B shows that the price decline between the beginning of 2020 and the end of 2023 is larger for CMBX bonds with more office exposure.

Extracting precise conclusions from the evolution of CMBX prices for the underlying values of office properties is very difficult for at least four reasons. First, CMBX tranches are portfolios of 25 CMBS bonds, each of which is a derivative on its own unique combination of typically around 50-100 commercial mortgages backed by a range of collateral assets. Each of these commercial mortgages has its own default risk, which depends on the features of that mortgage. But the

Figure A8. : Price of CMBX Insurance and Office Exposure



Panel A: CMBX Prices

Panel B: Office Exposure

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

likelihood of default of the BBB- tranche depends on the joint default probability and loss-given-default distribution of all loans in the pool. Hence, there is a complex relationship between a loss in asset value for the offices that collateralize the CMBS loans and the losses on the CMBX BBB- tranche. One could try to study prices of Single Asset Single Borrower (SASB) deals that have one or more office assets as collateral, but the market for SASB tranches is substantially less liquid.

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

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

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

A7. Financial Fragility: Banks' CRE Exposure

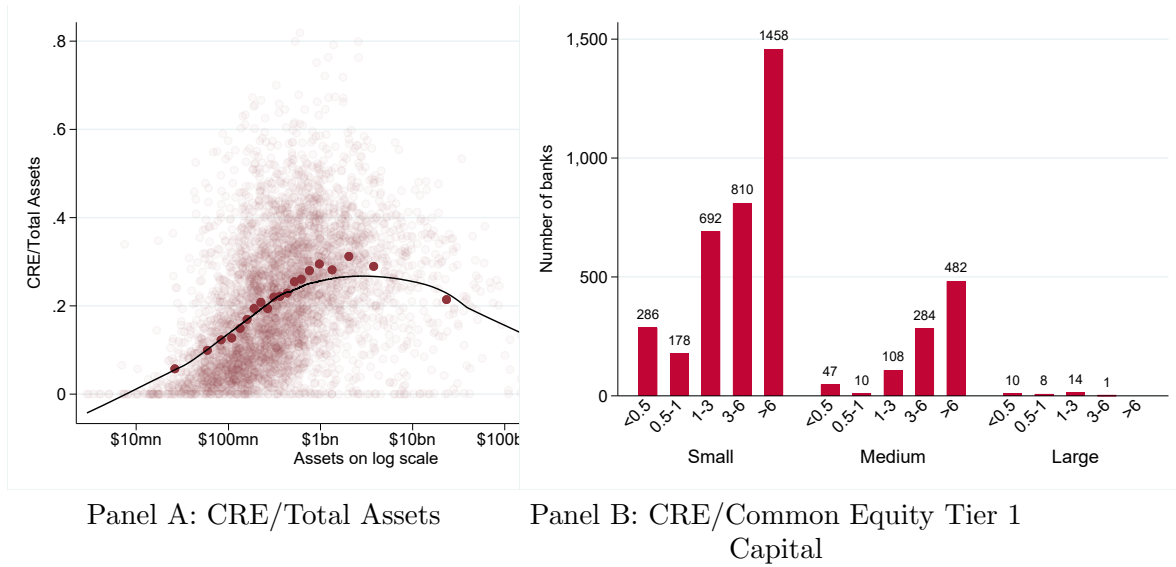
In this section, we explore some of the implications of CRE debt exposure for banks, who bear much of the debt exposure.

We measure bank size by bank assets and banks' commercial real estate (CRE) exposure by their outstanding commercial real estate loans, using Call Report data at the end of 2023.Q4 ([FFIEC, 2024](#)). We measure CRE loans using the variable "UBPRD489," which is the sum of (i) construction and land development loans, (ii) nonfarm nonresidential mortgages, (iii) unsecured loans to finance commercial real estate, construction and land development, (iv) other real estate owned, and (v) investments in unconsolidated subsidiaries and associated companies. We use the variable "UBPRP742" to measure common equity tier 1 capital, which is the sum of common stock and related surplus, net of treasury stock and unearned employee stock ownership plan (ESOP) shares.

Panel A of Figure [A9](#) shows CRE loan exposure as a share of bank assets (vertical axis), plotted against log bank assets (horizontal axis) as of 2023.Q4. Each dot represents one bank. CRE exposure is inverse-U shaped in bank size, with the largest concentration of CRE risk in banks with around \$1 billion in assets. Panel B shows the number of banks with different ratios of CRE loans to common equity tier 1 capital (< 50%, %50 – 100%, 100% – 300%, 300% – 600%,

> 600%) for small, medium, and large banks. Among small and mid-sized banks, a large fraction has CRE exposure that exceeds the supervisory threshold of 300% of tier-1 capital in CRE loans. Several hundred mid-size banks have a ratio that exceeds 600%. None of the large banks have this much exposure to CRE credit risk.

Figure A9. : Commercial Real Estate Exposure By Bank Size



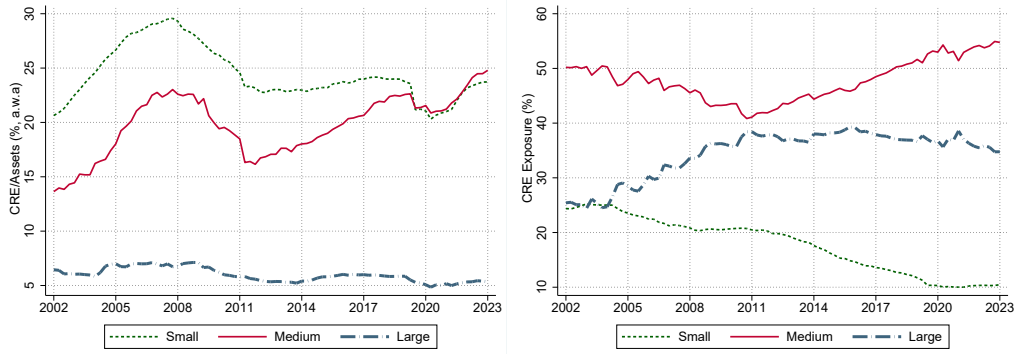
Notes: Panel A shows the ratio of commercial real estate loans to bank assets plotted against the log of bank assets for U.S. banks as of 2023.Q4. Panel B shows the number of banks as of 2023.Q4 within different categories of commercial real estate loans to common equity tier 1 capital (< 50%, 50% –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

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

Table A5—: Commercial Real Estate Exposure by Bank Size

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

Figure A10. : Commercial Real Estate Exposure of Banks over time



Panel A: CRE/Total Assets

Panel B: CRE Exposure (%)

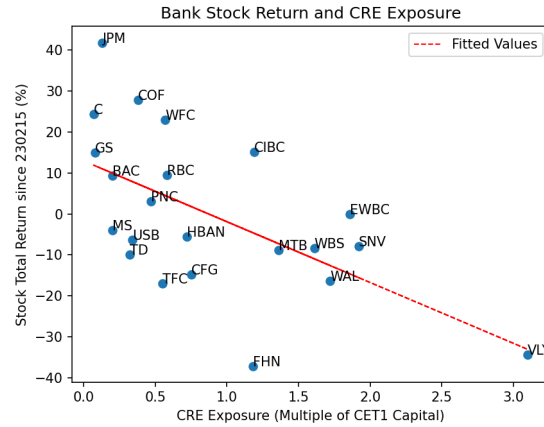
Notes: Panel A shows commercial real estate loans as a proportion of total assets by bank size over time. We show three different bank sizes: Small (\$ < 1 billion in assets), Medium (\$1 – \$100 billion), and Large (\$ > 100 billion). Banks are divided into these groups in each quarter using assets expressed in 2023.Q4 dollars ([U.S. Bureau of Economic Analysis, 2024](#)). Within each category, we plot the asset-weighted average. Panel B shows the share of overall CRE loans held by each group over time. Data are sourced from the Call Reports.

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

Next, we consider the implications of CRE holdings on bank equity exposure, for publicly listed banks. We focus on the period around the collapse of Silicon Valley Bank (SVB), at which point the markets began to price in commercial

real estate exposure. Figure A11 below shows that the stocks of banks with large CRE exposure in late 2022 indeed experienced much lower stock returns over the ensuing period. These results highlight the broader spillovers of commercial real estate exposure on other intermediaries.

Figure A11. : Bank Stock Return and CRE Exposure



Notes: The figure shows the cumulative stock return between Feb 15, 2023 and Apr 4, 2024 and the CRE exposure of the top U.S. banks. The data source of stock return is Bloomberg, and the data source of CRE Exposure is JP Morgan ([JP Morgan, 2023](#)). CRE exposure is defined by CRE loans as of Q3'22 excluding owner-occupied, construction and land development, farm, and multi-family loans.

MODEL DERIVATION

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

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

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

B1. Revenue

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

which is the law of motion of R_t^O .

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

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

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

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

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

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

We define scaled revenues as

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

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

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

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

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

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

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

The scaled version of revenues can be written as:

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

which solves the following Bellman equation:

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

Finally, we get V_t^R by

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

B2. Costs

The building costs are written as:

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

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

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

We define scaled costs as:

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

Therefore, we have:

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

where

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

The expected PDV of costs is written as:

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

The scaled version is:

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

which solves the Bellman equation

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

Finally, we get V_t^C by

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

CALIBRATION ALGORITHM

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

C1. NYC All, given p

- 1) Keep only office buildings and exclude subleases in the CompStak data set of leases for NYC.
- 2) Calculate the average lease term for all leases in NYC. Set χ equal to the reciprocal.
- 3) Estimate ε from data:
 - a) To estimate $\varepsilon(E)$ and $\varepsilon(R)$, first calculate NER series for each month controlling for submarket, tenant industry, leasing type, and building class FEs, and take the 6-month moving average. Use data from January 2000 (start of CompStak) until December 2019.
 - b) If more than 6 months of the 1-year rolling window falls in recession, then that rolling year is considered to be a recession; otherwise it is considered to be an expansion. We use the leasing cycle definition instead of the business cycle.
 - c) Compute the annual growth rate of the six-month moving average rent, and take the average separately for expansions and recessions.
 - d) Estimate $\epsilon(WFHR)$ as the annualized realized NER growth between March 2020 and December 2020, and $\epsilon(WFHE)$ as the annualized realized rent growth between December 2020 and December 2023.
- 4) Estimate $\eta(E)$ and $\eta(R)$ from data:
 - a) Compute the growth rate in floor space in year t as the newly constructed office square feet in year t relative to the total square feet of office space built before year t . We look at growth after 1950 for NYC All.
 - b) Year t is a recession when more than six months of that year is in recession.

- c) We take the average the construction growth rate separately for expansions and recessions.
 - d) Finally, we subtract the rate of depreciation to arrive at $\eta(E)$ and $\eta(R)$.
- 5) Set $\eta(WFHE) = \eta(E) + \Delta\eta$ and $\eta(WFHR) = \eta(R) + \Delta\eta$. We choose $\Delta\eta = 1\%$ to capture two forces that drive the supply side response post the WFH shock: (1) The excess office supply resulting from remote and hybrid work would create a transitory reduction in supply growth. We calibrate this impact by matching the average supply growth reduction in NYC, following another large demand reduction in office, namely the Great Financial Crisis. The supply growth from 2010 to 2019 in NYC was -0.5% below the long-term average in the regular expansion state. (2) Additionally, some of the office stock will be converted to other usages and reduce the total supply. We calibrate the conversion rate to be 0.5% annually based on the realized conversion in the past four years. CBRE reports that in 2023.Q4 the planned/underway office conversion ratio in the U.S. is around 2% . Within those conversion projects, a small number of them may have started before the pandemic. However, we also expect an acceleration of office conversion in the coming years, given the sluggish nature of supply responses. Therefore, we choose to average the 2% across four years, or 0.5% per year, to obtain the annual office conversion rate. We provide sensitivity analysis on the choice of $\Delta\eta$ in Section D.D10.²⁵
- 6) Estimate the four parameters $\{s^O(E), s^O(R), s^V(E), s^V(R)\}$ to match the following four moments in quarterly Manhattan office occupancy rate data for from 1987.Q1 to 2019.Q4:
- a) empirical mean
 - b) empirical standard deviation
 - c) empirical min - 0.5%
 - d) empirical max + 0.5%
- 7) Assume that the four parameters $\{s^O(WFHE), s^O(WFHR), s^V(WFHE), s^V(WFHR)\}$ are shifted by a common factor δ relative to their no-WFH counterparts: $s^{\{V,O\}}(WFH) = \delta \cdot s^{\{V,O\}}(no-WFH)$. Estimate the parameter δ to best fit the dynamics of the office occupancy rate in the 16 quarters from 2020.Q1–2023.Q4. The first 4 quarters are WFH-R and the last 12 are WFH-E. The dynamics are given by the model:

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

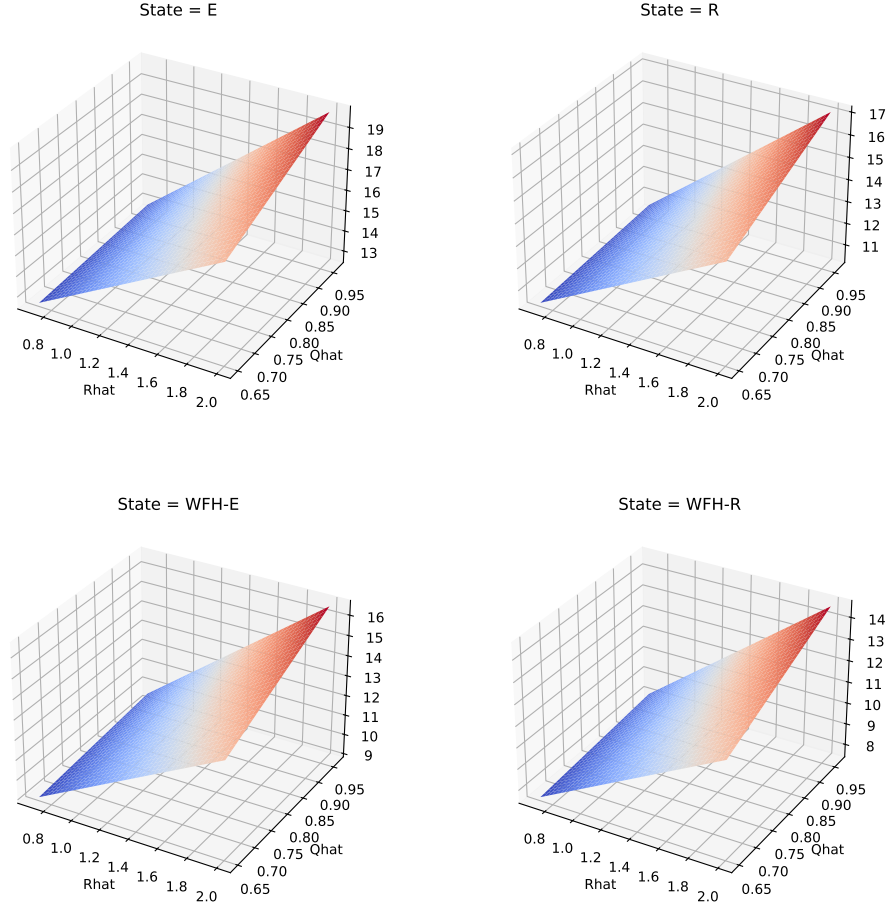
²⁵Source: <https://www.cbre.com/insights/briefs/more-office-conversions-underway-to-revitalize-downtowns>.

C2. NYC A+, given $\Delta\eta$

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

4. When calculating η for A+ buildings, we collect all the buildings that have ever entered into the A+ universe, given our time-varying definition of A+ buildings, and re-do the calculation for NYC All. Since A+ is only a subset of NYC market, we start the calculation of η for each year from 1970 to 2019 to avoid extreme value caused by lack in coverage.
5. The NYC A+ calibration takes $\Delta\eta$ from the NYC All calibration.
6. We use data from NAREIT on the U.S. office sector occupancy from 2000.Q1 to 2019.Q4 to calibrate $\{s^O(E), s^O(R), s^V(E), s^V(R)\}$. We target a minimum occupancy rate that's lower than the empirical min in this sample period, because the A+ occupancy data is missing in the 1990s, which is the worst historical period for office occupancy. We assume that both A+ and the entire Manhattan office market experienced the same number of standard deviation decline from their mean since 2000 when they reached their own minimum in the 1990s.
8. Given all other parameters, find p to match the observed realized return on NYC-centric office REITS between December 31, 2019 and December 31, 2020, after adjusting for leverage. See the discussion in Section III.C.

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

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

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

MODEL RESULTS

D1. Model Outcomes for the NYC All Market

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

In a Gordon Growth Model with constant expected NOI growth rate g and a constant discount rate r , the cap rate $c = r - g$. Our Markov Chain model features time-varying expected growth and time-varying expected office returns, so this relationship does not hold. It is nevertheless useful to look at the two components of the cap rate. The model implies an expected return on NYC office of 8.17% and an office risk premium of 7.63%. This is naturally lower than the equity risk premium of 10.54% since an unlevered office property is less risky than the aggregate stock market (which is a levered investment). The office risk premium is substantially higher in recessions (12.88%) than in expansions (6.47%). Expected NOI growth is 1.33% unconditionally. This number is in real terms and incorporates that the office stock depreciates, so that real NOI growth is 3.89% before depreciation ($=1.33\%+2.56\%$). Expected cash flow growth is higher in expansions than in recessions. While the likelihood of transitioning from a recession to an expansion state is reasonably high, the NOI growth rate conditional on staying in the recession state is very negative while the NOI growth conditional on leaving the recession state is only mildly positive.

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

The last part of the table shows the value of the building, scaled by potential rent, and broken down into the PDV of revenues minus PDV of costs. The typical NYC office trades for a multiple of 6.87 times potential gross rent unconditionally according to our calibration. The average valuation ratio of office properties in the E state of 7.01 is 33.62% higher than the value of 5.25 in the WFH-R state.

D2. Model Results for NYC A+ Market

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

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

Table A6—: Model Solution for NYC All Calibration

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

Table A7—: Calibration for NYC A+

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

Table A8 shows the model solution for the A+ calibration. The model delivers a lower cap rate for A+ NYC office, due to the lower riskiness of A+ cash flows. Class A+ has lower vacancy levels than the NYC market as a whole, on average as well as in the WFH states.

D3. Calibration to Other Markets

We repeat the calibration procedure discussed in the main text and in Appendix C for San Francisco and Charlotte. We use CompStak data to measure market rent growth, ϵ , before and during the pandemic. We also use CompStak data to measure pre-pandemic office construction rates (η is the construction minus the depreciation rate). Like in the NYC calibration, net supply growth rates during the transition (WFH-R and WFH-E) are set equal to their pre-2020 counterparts (R and E) minus an adjustment factor $\delta\eta$, set equal to the NYC one. Due to the incomplete building coverage in CompStak, estimation of η for San Francisco and

Table A8—: Model Solution for NYC A+ Calibration

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

Charlotte starts in 1980. We use contractual occupancy rate data from Cushman and Wakefield to calibrate s^O and s^V .²⁷ We leave the office depreciation rate and the operational cost parameters the same as in the NYC calibration. Naturally, we assume that the dynamics of the aggregate state variable $\pi(z', z)$ are common across markets, as well as the market prices of risk $M(z', z)$.

Table A9 shows the calibrated parameters for San Francisco and Table A10 those for Charlotte. Tables A11 and A12 show the main moments for San Francisco and Charlotte, respectively. The SF office market is riskier than the NYC market, featuring a rent cycle of greater amplitude which translates into a higher risk premium and cap rate. Charlotte is less risky than the SF market. Figure A13 plots fan charts for occupancy rates, revenues, NOI and cap rates for San Francisco and Charlotte.

Table A9—: Calibration for San Francisco

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

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

Table A10—: Calibration for Charlotte

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

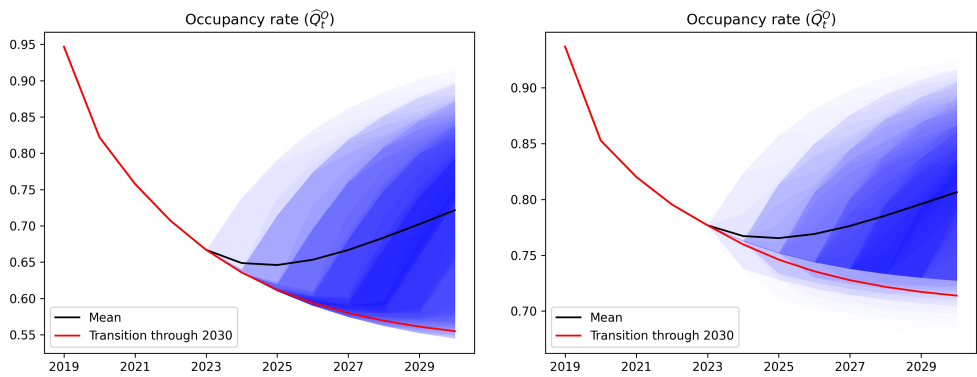
Table A11—: Model Solution for San Francisco Calibration

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

Table A12—: Model Solution for Charlotte Calibration

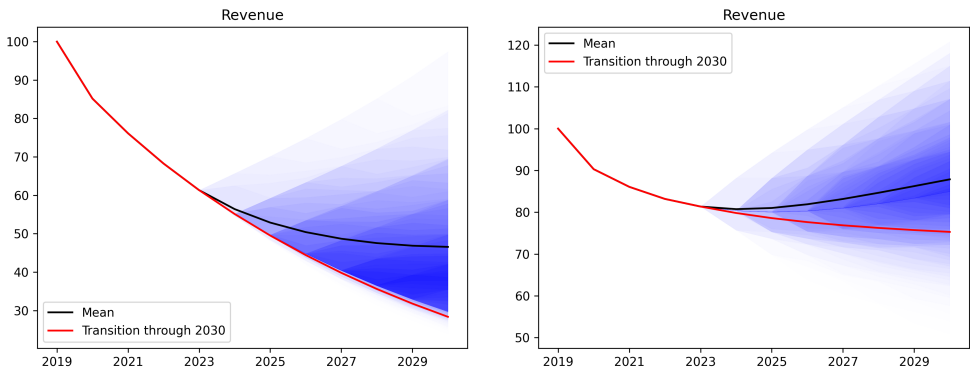
Statistic	Uncond	E	R	WFHE	WFHR
Cap rate	0.0891	0.0839	0.1130	0.0741	0.0966
Office $\mathbb{E}[Ret] - 1$	0.0968	0.0765	0.1912	0.0688	0.1781
Office RP = $\mathbb{E}[Ret] - 1 - R_f$	0.0914	0.0777	0.1541	0.0699	0.1409
$\mathbb{E}[g_t]$	-0.0020	0.0099	-0.0574	-0.0194	-0.0648
Vacancy rate = $1 - \widehat{Q}^O$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

Figure A13. : Fan Charts for San Francisco and Charlotte



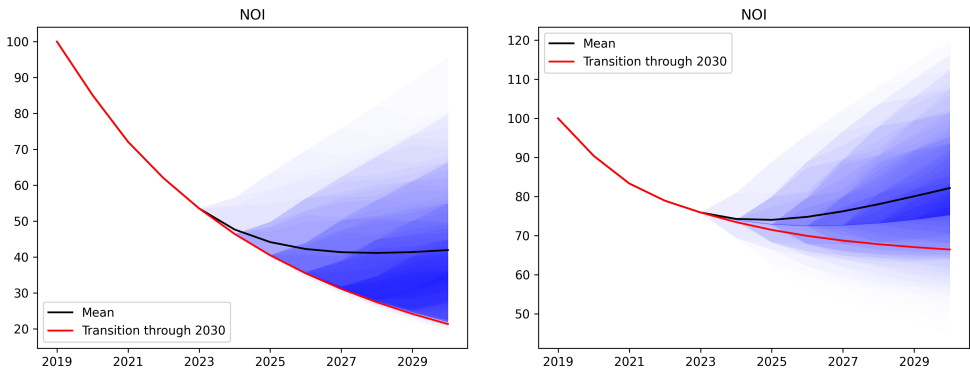
(a) San Francisco: Occupancy

(b) Charlotte: Occupancy



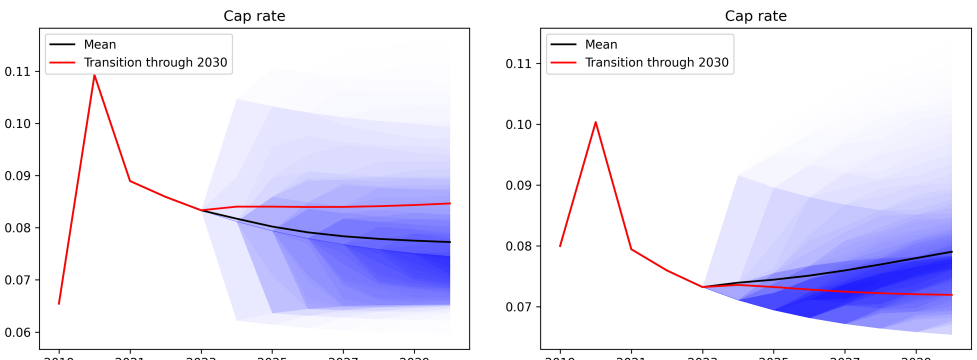
(c) San Francisco: Revenue

(d) Charlotte: Revenue



(e) San Francisco: NOI

(f) Charlotte: NOI



D4. Counterfactual Analysis of WFH Intensity in NYC

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

To discipline this exercise, we utilize the reduced-form estimates of the impact of WFH on city occupancy rates and NER. We expect heterogeneity in the treatment effect of firms' WFH plans on occupancy and rents across cities. Intuitively, firms in cities with high-population density may find it more costly to not share desks among hybrid workers or to increase the amount of common spaces. Indeed, Table A13 shows stronger treatment effects of variation in the remote working index on occupancy and rent in high-density areas (U.S. Census, 2024). Since our baseline model is calibrated to high-density New York City, we use the sum of the estimates in the first and last rows of columns (2) and (4). We get similar results if we do not consider the heterogeneity by density or if we capture the heterogeneity using MSA-level commute times instead.

Table A13—: Remote Work and Office Space Demand/Rent

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

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

We use these occupancy and rent sensitivity coefficients for high-density areas to re-calibrate the model parameters (ε , δ) under different counterfactual WFH days in NYC. For supply growth, we assume that each additional WFH day will

reduce supply growth by -0.5% ($\Delta\eta$). Table A14 reports the resulting parameters for each change in WFH days relative to the benchmark. The row “0.0” is the benchmark model. All these model variants have the same parameter p . The parameter variations kick in in 2020, after the economy has entered the WFH transition.

Table A14—: Counterfactual Calibration for NYC All

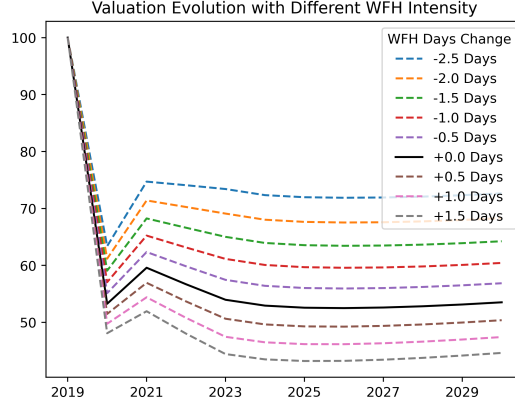
Δ WFH Days	ϵ		η		s^o		s^v	
	WFHE	WFHR	WFHE	WFHR	WFHE	WFHR	WFHE	WFHR
-2.5	-0.001	-0.154	-0.013	-0.012	0.765	0.337	0.161	0.275
-2.0	-0.005	-0.158	-0.015	-0.014	0.699	0.308	0.147	0.251
-1.5	-0.009	-0.162	-0.018	-0.017	0.635	0.280	0.134	0.228
-1.0	-0.013	-0.166	-0.020	-0.019	0.572	0.252	0.120	0.205
-0.5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

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

Figure A14 shows the results for the mean office valuation in the NYC All market. As always, they are conditional on the state of the economy in 2020 being WFH-R and the states in 2021–2023 being WFH-E. Recall that the Kastle data shows that the physical office occupancy in NYC is around 50% at the end of 2023, suggesting that the average office tenant in NYC may have an average of 2.5 remote working days. The valuation drop after the WFH shock shrinks significantly when the average WFH days are reduced by a day or more.²⁸ Conversely, each additional remote work day relative to the benchmark model further lowers office values. In conclusion, this exercise shows that intensive-margin variation in working-from-home days has large implications for office values.

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

Figure A14. : WFH Intensity Counterfactual Analysis



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

D5. Sensitivity to Expected Length of Transition

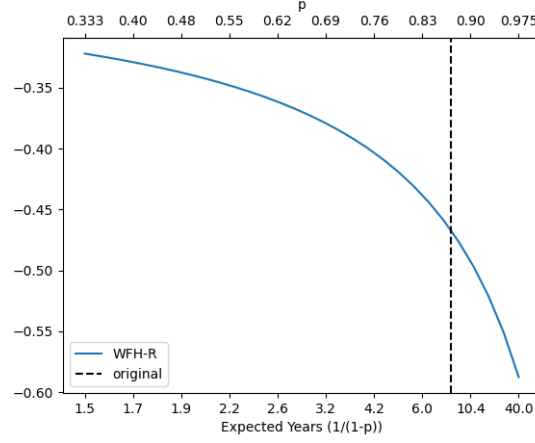
Figure A15 plots the NYC office value decline in 2020 for various values of the parameter p , indicated on the top horizontal axis. The bottom horizontal axis reports the expected length of the transition, $(1 - p)^{-1}$. The vertical dashed line indicates our benchmark model with $p = 0.875$, which produces a 46.73% valuation decline in the transition.

D6. Sensitivity to WFH-R Rent Growth

Figure A16 shows the office valuation for NYC All for the average sample path under an alternative assumption on NER growth in the WFH-R state, namely that it equals the NER growth in a regular recession state R. The impact on the model prediction is modest.

D7. Priced Transition Risk

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

Figure A15. : Change in Valuation with Different p for All NYC

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

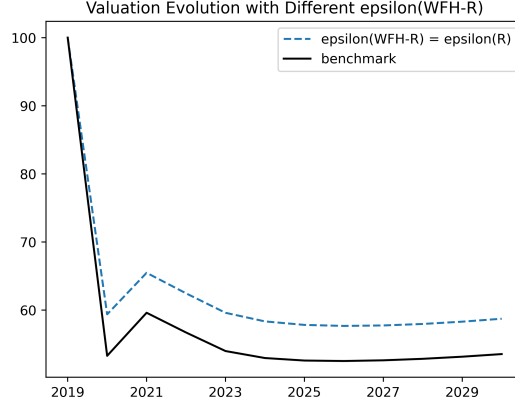
The one-period SDF is then determined by both the price of business cycle risk M^{BC} and the WFH risk shifter M^{WFH} :

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

To keep this calibration simple, we assume that the WFH transition risk increases the equity risk premium by a constant amount rp_{wfh} , and back out the restrictions on $M^{WFH}(z'|z)$ for each state (z, z') that accomplish this.²⁹ We consider a plausible range for rp_{wfh} ranging from -1% to 5% per year. When the rp_{wfh} is positive, WFH transition states are bad states of the world and high marginal-utility states for the representative agent. Cash flows in the WFH transition period are then more valuable: $M_{TT} > M_{TN}$. This scenario is consistent with the inference in [Monte, Porcher and Rossi-Hansberg \(2023\)](#) based on a structural urban model, who argue that the shift to more WFH reduced aggregate welfare.

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

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

Figure A16. : Setting $\epsilon(WFH - R) = \epsilon(R)$ 

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

as follows:

	Normal-E	Normal-R	Transition-E	Transition-R
Normal-E	R_{EE}	R_{ER}	Not relevant ³⁰	
Normal-R	R_{RE}	R_{RR}		
Transition-E	$R_{EE} + \frac{1+p}{1-p}rp_{wfh}$	$R_{ER} + \frac{1+p}{1-p}rp_{wfh}$	$R_{EE} - rp_{wfh}$	$R_{ER} - rp_{wfh}$
Transition-R	$R_{RE} + \frac{1+p}{1-p}rp_{wfh}$	$R_{RR} + \frac{1+p}{1-p}rp_{wfh}$	$R_{RE} - rp_{wfh}$	$R_{RR} - rp_{wfh}$

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

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

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

Since the probability of transitioning from the E or R states to the WFH-E and WFH-R is zero, the Euler equations for the stock return in the E and R states are uninformative for M^{WFH} . Hence, we normalize $M_{NN} = M_{NT} = 1$. The remaining two parameters M_{TN} and M_{TT} enter in four Euler equations: the Euler equation for the equity return in the WFH-E state, the Euler equation for the equity return in the WFH-R state, the Euler equation for the risk-free rate

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

Table A15—: Calibration Result of WFH Transition Risk

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

in the WFH-E state, and the Euler equation for the risk-free rate in the WFH-E state. We choose the values for M_{TN} and M_{TT} that minimize the root mean squared stock Euler equation errors and the risk-free rate errors, weighting the WFH-E moments by 0.823 and the WFH-R moments by 0.177, which are the relative likelihoods of expansions and recessions. It turns out that we can set $M_{TT} = 1$ without increasing these four Euler Equation errors. The first column in Table A15 reports the best-fitting remaining parameter M_{TN} , while the second column reports the weighted root mean squared error in percent per year.

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

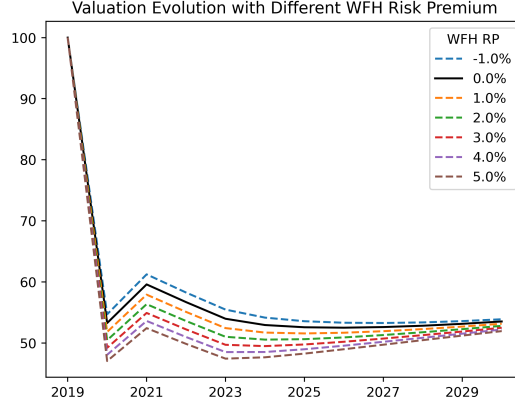
The last two columns of the table show what the model with priced transition risk implies for the immediate value drop (2020 versus 2019) and for the long-run value drop (2030 versus 2019) of the NYC All office stock. The first row with $rp_{wfh} = 0$ is the benchmark model.

Figure A17 shows the office valuation of NYC for WFH risk premium values from -1% to 5% per year. Intuitively, higher WFH risk premium represents that WFH is a worse state, and thus the office market has a lower valuation. The office market provides higher total return (NOI + capital gain) required by the market through adjusting to a lower value at first. We can also observe that priced WFH risk has low quantitative importance for our result: The average valuation paths of different WFH risk premia stay close to the benchmark case (0% risk premium), and eventually converge to the benchmark in the long-run. The evolution of the cash flow dominates the valuation of the office market during and after the WFH transition period.

D8. Shutting Down Business Cycle Risk

Figure A18 shows the valuation impact in a model where the pricing of cash flow is independent from the business cycle. We compute this model by setting

Figure A17. : NYC All Valuation with Priced WFH Risk



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

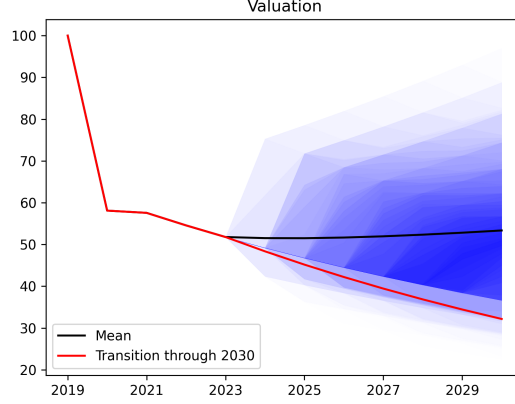
M^{BC} such that we match the same unconditional equity return of 11.08% in both expansions and recessions, and that the state prices in all four transition states are the same.³¹ The impact on the value decline of NYC office is -41.90% in 2020 and -46.65% in 2030, relative to pre-pandemic levels. The corresponding numbers in the benchmark model are -46.73% and -46.47%. The slightly smaller short-term valuation effect arises because the state-invariant business cycle (equity) risk premia raise the discount rate in expansion, and thus leads to shorter effective duration of the stream of office cash flows in 2019, which weakens the valuation impact of a given decline in cash flows. Indeed, the cap rate in 2019 is 9.14% in this model compared with 5.78% in the benchmark model. This difference in the valuation impact narrows in the long-term, because the unconditional discount rate is the same as the one in the benchmark model.

D9. Fixed WFH Transition Length

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

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

Figure A18. : Shutting Down the Business Cycle Risk



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

function of 0 remaining years (ry) in the WFH transition period, we iteratively solve for the value function with $ry = 1, 2, 3, \dots$ remaining years in the WFH transition period using backward induction:

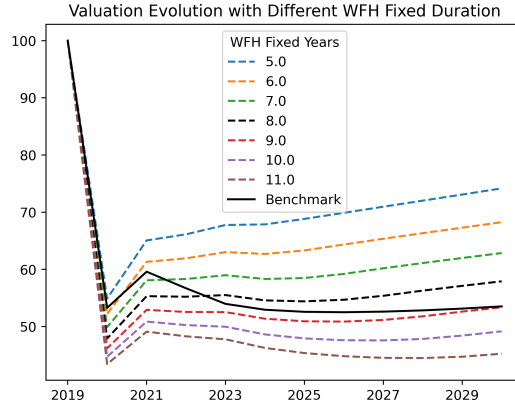
$$\hat{V}(ry, z, \hat{Q}, \hat{R}) = \mathbb{E} \left[M(z') \left[\widehat{NOI}(z', \hat{Q}', \hat{R}') + \hat{V}(ry - 1, z', \hat{Q}', \hat{R}') \right] \right].$$

Figure A19 shows the mean office valuation in the NYC All market, conditional on the state of the economy in 2020 being WFH-R and the states in 2021–2023 being WFH-E. The average office value decline is modestly higher when the transition ends in $1/(1-p) = 8$ years for certain (-52.09% in 2020 vs. -46.47% in the benchmark model). The opportunity of early exit is more valuable than the protection from late exit, so that the uncertainty about the length of the transition period ends up benefiting the valuation. This is because vacancy growth decelerates while the strength of reversal accumulates with more time in the WFH transition period.

In 2020, the certainty equivalent of the uncertain transition length is around 5 years. The mean valuation path of the benchmark model (solid black line) overlaps with the mean valuation path under fixed transition length of 6 years (dashed orange line), which has 5 years remaining in transition at the end of 2020. The certainty equivalent changes over time. It drops to around 4.5 years at the end of 2023, with the benchmark's solid black line halfway in between the dashed black line (8 years of transition, 4 years of transition remaining at the end of in 2023) and dashed red line (9 years of transition, 5 years of transition remaining at the

end of in 2023).³² The upside of uncertainty (exit out of the transition) becomes more valuable than the downside (staying in transition) over time. However, note that we are only examining the cash flow risk of WFH transition here. If the discount rate (WFH risk premium) drops when the uncertainty about the length of the transition period is removed, the certainty equivalent of the uncertain WFH transition period will become higher. See Appendix D.D7 for details.

Figure A19. : Fixed Length of WFH Transition Period



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

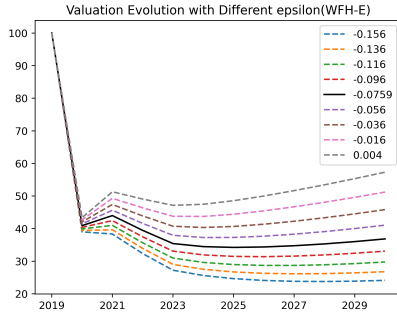
D10. Robustness Tests for San Francisco

Figure A20 performs four sensitivity analyses for San Francisco. Panel (a) varies $\varepsilon(WFH - E)$, the rent growth rate in the WFH-E state. Panel (b) varies $\Delta\eta$, the gap between net supply growth in the transition regime relative to the pre-2020 regime. Panel (c) varies the expected length of the transition period governed by the parameter p . Panel (d) introduces a floor for office values set at 30% of 2019 valuations. The latter exercise is a simple way to model additional optionality from adaptive reuse not already captured by the net supply

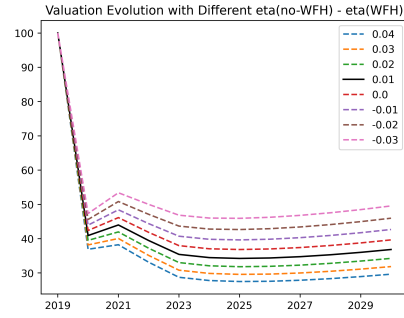
³²Note that 2023 is the last year we can infer the certainty equivalent transition length because only years up until 2023 are in WFH transition for certain in the benchmark model. The evolution to the right of 2023 is not informative about the effect of the uncertainty about the transition period. First,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

parameter η . This specification is intended to capture the redeployability option, as office buildings may ultimately be converted to other uses. We use 30% as a rough benchmark for the option value to covert to other uses. A fuller consideration of this option—which will be affected by interest rates, costs of conversion, and demand for other uses among other factors—is outside of the scope of our analysis, which is focused on valuing cash flows resulting from buildings operated as commercial office buildings. [Gupta, Martinez and Van Nieuwerburgh \(2023\)](#) studies conversions from office to residential in detail.

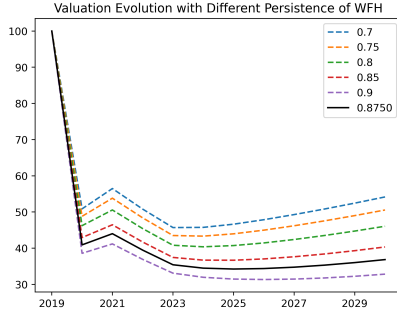
Figure A20. : Robustness Tests for San Francisco



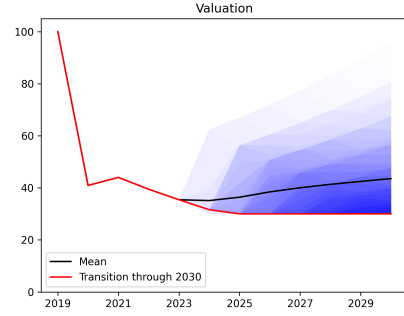
(a) Different $\epsilon(WFH - E)$



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



(c) Different Persistence of WFH



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

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