# Lease Expirations and CRE Property Performance*

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**Abstract**

We study how lease expirations affect the performance of commercial real estate properties and how these patterns changed during the COVID-19 pandemic. Even before the pandemic, lease expirations produced notable downside risks to property occupancy and income, particularly in weaker property markets. These risks became more pronounced during the pandemic, driven by office properties; office occupancy deteriorated 50 percent more during the pandemic following lease expirations, with even larger effects in Central Business Districts (CBDs). We use these estimates to project future vacancy rates under different scenarios. We find that risks to CBD office occupancy are substantial, but highly sensitive to assumptions about the rate at which leasing dynamics will normalize. As regional and community banks' office loan exposure is largely located outside of CBDs, this geographic pattern may mitigate the severity of CRE credit losses for these banks.

Keywords: Commercial real estate, lease expirations, COVID-19, office loans, bank loan exposure
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# 1 Introduction

The COVID-19 pandemic has the potential to significantly disrupt the commercial real estate (CRE) market. In particular, the pandemic-induced rise in remote work appears to have led to a large and persistent decline in the demand for office space, especially in central business districts (CBDs). However, CRE loan performance remained relatively resilient during the first few years of the pandemic, as long-term leases temporarily shielded commercial-property owners from the full ramification of the weaker demand for space. How these properties will perform in the longer term as more leases expire remains an open question. To shed light on this issue, we analyze how lease expirations have affected property performance historically and investigate how these patterns have changed since the COVID-19 outbreak.

We find that, before the pandemic, lease expirations were associated with modest deterioration in a property's financial performance. A property with expiring leases accounting for 10 percent of its square footage would be expected to experience a roughly 80 basis point decline in its occupancy rate and net operating income (NOI) growth following the expiration. These declines predominantly reflect downside risk; lease expirations have little effect on median or better outcomes of property performance, but they are associated with notable declines in occupancy and income at lower quantiles.

These effects of lease expirations are highly dependent on the strength of the local property market. In markets with minimal vacancy, expirations bring about little change in occupancy and even modest increases in income. However, when market vacancy rates are relatively high, expirations are associated with more dramatic declines in income and occupancy. Intuitively, when local supply outstrips demand, expiring leases are less likely to be renewed or replaced at a comparable rent. Even when landlords do manage to lease the space again, costlier concessions are needed to do so, resulting in weaker cash flows after the expiration.

This dynamic implies that the outcome of recent lease expirations can provide a valuable signal about the strength of demand in a local property market. For example, to the extent that demand for office space has fallen structurally due to the pandemic, we would expect the financial performance of office properties to deteriorate more substantially when leases expire. Even before enough leases have rolled over to cause a significant deterioration in property performance, an environment characterized by difficulty retaining tenants upon expiration can signal more distress to come.

To investigate the extent to which the pandemic has stressed CRE markets, we examine how the response of CRE property performance to scheduled lease expirations differs in the pandemic and pre-pandemic periods. We find that, over all property types, expirations during the pandemic have so far had only modestly larger effects on occupancy or income compared with the period before the COVID-19 outbreak. However, some segments show clear signs of strain. For offices, lease expirations reduced occupancy by over 50 percent more during the pandemic, and reduced NOI growth by twice as much. These effects vary substantially across localities: the adverse effect of lease expirations on occupancy or income more than doubled for office properties in CBDs relative to the effect before the pandemic. Additionally, we find that COVID-era lease expirations cause a greater deterioration in property performance in counties where there has been a greater decline in time spent at workplaces, and properties that have not been recently renovated (consistent with a flight-to-quality effect).

Finally, we conduct two exercises to investigate the longer-term implications of these findings for office property performance and bank credit risk exposure. First, we use the coefficient estimates to calibrate a simple model of occupancy dynamics, which we then use to project future changes in vacancy under different scenarios. Under the most adverse scenario—where the rates at which tenants renew expiring leases and landlords fill vacant space remain permanently depressed—steady-state vacancy rates rise by about 7 and 27 percentage points (relative to pre-COVID levels) for suburban and CBD offices, respectively. The projected rise in vacancy rates is smaller under the (presumably more realistic) assumption that leasing dynamics improve over time as asking rents fall, and the supply of office space adjusts downward, and remote-work-heavy firms exit the tenant pool. If parameters pertaining to tenant exit and space filling revert to their pre-COVID values at a rate of 10 percent per year (roughly the rate at which leases and CRE loans turn over), vacancy rates would peak at about 4 and 10 percentage points above pre-COVID levels for suburban and CBD offices, respectively.

Second, we examine the extent to which different types of lenders are exposed to vulnerable CRE loan segments. We show that small and regional banks have on average a lower share of their office loan portfolios in the most at-risk areas—that is, CBDs and localities with a greater shift to remote work—relative to other CRE lenders. Though this benefit is partially offset by smaller banks lending against more outdated, and lower-value properties, we still estimate that leasing dynamics deteriorated less for offices securing smaller banks' loans. Thus, while office loans at small and regional banks still face headwinds from higher interest rates and difficulties in refinancing, the properties securing these loans at least appear to be located in markets with more favorable leasing dynamics. This geographic distribution should mitigate the risk of deteriorating office loan performance amplifying the strains on regional banks.

## 1.1 Related Literature

Broadly speaking, this paper contributes to three strands of research. First, we contribute to work analyzing frictions in leasing markets. Mooradian and Yang (2000); Yoshida et al. (2016) show that the lessees need to pay significant premiums for short-term leases or cancellation options, consistent with landlords requiring compensation for transaction costs associated with tenant turnover. Moszkowski and Stackman (2022) show that search frictions in leasing markets combined with substantial heterogeneity in match quality can produce long vacancy spells after tenants exit, as landlords wait to find a suitable tenant. We add to this work by directly testing how lease expirations affect property performance. Consistent with this literature, we show that the effects of lease expirations are significant, and skewed to the downside.

Second, we contribute to work studying the disruption to property markets posed by the COVID-19 pandemic. The pandemic caused a significant movement of people and businesses to lower density areas (Ramani and Bloom, 2021; Monte et al., 2023), resulting in adverse effects on property prices (Ghosh et al., 2022) and commercial rent (Rosenthal et al., 2022) in urban areas. Gupta et al. (2022) estimate that declines in leasing revenue due to the rise of remote work lowered the value of office buildings in the U.S. substantially. Our estimates provide more detail on the dynamics behind the decline in leasing activity. We estimate that there was both a sizable increase in the rate at which tenants exit when leases expire during COVID-19, and a decline in the rate at which vacant space is filled. Both of these effects are more pronounced in CBDs.

Third, we contribute to work quantifying the exposure of the banking sector to such CRE-market strains. Jiang et al. (2023) use information on commercial mortgage-backed securities (CMBS) loans with negative equity to quantify the extent to which CRE credit risk compounds bank solvency concerns. Acharya et al. (2023) note that impending CRE loan losses may add to other stresses already being felt by small and regional banks in the aftermath of the run on Silicon Valley Bank. We show that these banks are less exposed than CMBS loan pools to the markets where leasing activity has weakened the most (i.e., CBDs and localities with a larger shift to remote work). Thus, while the performance of bank CRE loans is likely to deteriorate going forward, this geographic pattern suggests that loan delinquencies at small and regional banks might be less severe than would be inferred from CMBS portfolio signals.

# 2 Data and Methodology

## 2.1 Data

We use panel data from Morningstar on properties securing CMBS loans to investigate the effects of lease expirations on property performance. CMBS are the second-largest category of funding sources for office properties in the United States (behind banks) and tend to specialize in larger loans.[1] This market segment is useful for our purpose because borrowers need to provide regular updates regarding their properties' financial performance and lease expiration schedule. Our sample contains office, retail, and industrial properties, the three property types for which lease expirations are important. The sample starts in 2009, when reporting of leasing variables began.[2]

While the data are reported monthly, the main variables of interest typically are updated at a lower frequency. At each lease-rollover review date, scheduled lease expirations are reported in one-year increments up to four years out. We measure pending lease expirations as of the last lease-rollover review date that is at least one year before the date financial data were updated. Measuring pending lease expirations using scheduled expirations from more than a year away addresses the sample selection concern that very-near-term expirations are observed only for tenants that do not extend their leases by that point.[3] Namely, we measure lease expirations from year $t$ to $t + 1$ using the year-ahead pending expirations as reported in the lease review of year $t - 1$.

Regarding property performance, we consider changes in occupancy and net operating income between the last financial update before the lease expiration window starts to the first update after that window ends (which we denote as $t_-$ and $t{+}1_+$, respectively).[4] As financials are typically updated annually, the outcome variable is generally the change in occupancy or income over the two year window containing the lease-expiration window. Details on how we measure lease expirations and changes in financials are provided in Appendix A.

Finally, we supplement the CMBS data with several geography-specific measures that help gauge the strength of local property markets. First, we use CBRE data on vacancy

[1]See Glancy et al. (2022) for a discussion of how CMBS loan portfolios differ from those of other major CRE lenders.

[2]Properties securing pari passu loans (loans split across multiple deals) appear multiple times in the data. We only keep one observation per property-month in such cases.

[3]Appendix Figure A.2 plots the distribution of scheduled lease expirations as of 2019. The density drops off considerably when the expiration is less than a year away, suggesting that some leases that would have had imminent expirations were renewed instead. By comparison, the density is fairly flat for expirations that are more than a year away. Consequently, scheduled lease expirations that are more than a year away should reflect the timing of previous contract arrangements rather than endogenous renewal decisions.

[4]We drop observations where the financial update is more than 1.5 years after the end of the lease expiration window in order to guarantee that we are consistently examining the near-term effects of expirations.

rates in major property markets as of the start of each financial reporting window (denoted Market Vacancy$_{i,t_-}$). This measure of vacancy is defined broadly as the share of space in the market currently available for leasing.[5] It is used to examine possible heterogeneity in the effects of lease expirations depending on how tight the local property market is.

Second, we use geographic variables to capture likely heterogeneity in the contraction in demand for office space during COVID. Central Business District$_{z(i)}$ is an indicator variable for whether $i$'s ZIP code is in a submarket CBRE identifies as being in a CBD. To capture cross-city differences in remote work patterns, Work From Home$_{c(i)}$ measures the decline in time spent at workplaces in a county relative to before the pandemic based on Google's Community Mobility Reports.[6] We also supplement these geographic measures with property-specific quality measures to capture potential flight-to-quality effects: Unrenovated$_{i,t_-}$ is an indicator for whether the most recent construction or renovation was over 20 years ago, and ln(Price Per Sq Ft)$_{i,t_-}$ measures the (log) valuation of the space as of the most recent appraisal before the financial-reporting window starts. These variables are included to reflect the increased preference for newer and higher amenity office properties during the pandemic (Gupta et al., 2022).

## 2.2 Methodology

To analyze the effects of lease expirations and how they changed during the pandemic, we estimate equations along the lines of:

$$\begin{aligned} Y_{i,t_-,t+1_+} = \alpha_{p,t} + \text{Expirations}_{i,t,t+1} \times \left(\gamma_0 + \sum_{j\in J}\gamma_j Z_{j,i,t}\right) \\ + \text{COVID Expirations}_{i,t,t+1} \times \left(\beta_0 + \sum_{j\in J}\beta_j Z_{j,i,t_-}\right) \\ + \eta' X_{i,t_-} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

[5]In addition to strictly vacant space, this availability measure also includes space available for sublease and marketed space currently under construction. We use availability for two reasons. First, unlike vacancy, it is reported for all property types. Second, it can more fully reflect tightness in the leasing market by accounting for the full range of space available to prospective tenants. There is an almost 1-to-1 correspondence between vacancy and availability when both measures are available (see Figure B.1), so we just refer to the availability rate as the market vacancy rate, since the latter terminology is generally more familiar.

[6]Work From Home$_{c(i)}$ is the decline (relative to the pre-pandemic period) in the average daily time spent at workplaces in property $i$'s county as of September 2022, the last full month for which data are available in Google's Community Mobility Reports (see Chetty et al., 2020). We use the last available data point to best capture the persistent change in remote-work patterns.

where $Y_{i,t_-,t+1_+}$ is the change in the occupancy rate or NOI growth for property $i$ over the roughly two-year period containing the lease expiration window. $\text{Expirations}_{i,t,t+1}$ is the share of leases (in terms of square footage) set to expire, and COVID $\text{Expirations}_{i,t,t+1}$ is the interaction of $\text{Expirations}_{i,t,t+1}$ with the pandemic indicator (equal to 1 if $t$ is 2020 or later). $\{Z_{j,i,t_-}\}_{j\in J}$ is a set of variables potentially affecting the sensitivity of property performance to lease expirations, and $X_{i,t_-}$ is a vector of controls that include the property vacancy rate at the start of the financial-reporting window as well as the non-interacted $Z_{j,i,t_-}$ variables. $\alpha_{p,t}$ is a property type-year fixed effect.

The key objects of interest are $\hat{\gamma}_0$, which estimates how lease expirations affect property performance in normal times, and $\hat{\beta}_0$, which estimates the degree to which expirations became more impactful during the pandemic. Additionally, coefficients on the interaction terms ($\hat{\gamma}_k$ and $\hat{\beta}_k$) allow us to quantify how certain factors, such as market vacancy rates or remote-work patterns, amplify the effects of lease expirations before or during the pandemic. In some specifications, we estimate equation (1) by quantile regression, in which case coefficient estimates pertain to how lease expirations affect various quantiles (rather than the expected value) of $Y_{i,t_-,t+1_+}$.

## 2.3 Summary Statistics

Summary statistics for the main variables of interest are reported in Table 1. It shows that leases associated with CMBS-funded properties are typically long term, and expirations tend to be lumpy. On average, about 10 percent of leases expire each year, but with a median of only 2 percent. This means that little space is typically covered by expiring leases, however, when leases do expire, they can be associated with a nontrivial fraction of space and thus can have large implications for the performance of the property.

Regarding property performance, occupancy for CMBS-funded properties tends to trend down slightly over time, while the rate of NOI growth is on average slightly lower than the rate of inflation.[7] The average property vacancy rate is about 8.3 percent, which is moderately below the average market-level vacancy rate of 13.7 percent. This difference partly stems from our measure of the market vacancy rate, which includes some new construction and space available for sublease. In addition, it could also partly reflect CMBS' comparative advantage in funding properties with higher-than-average quality, which generally have high occupancy rates (Black et al., 2017).

[7] NOI growth exhibits some extreme values, so we winsorize at the 1% and 99% levels.

# 3 Effects of Lease Expirations on Income and Vacancy

Before analyzing the effects of the COVID-19 pandemic, this section establishes the baseline estimates of how lease expirations affect property performance in normal times. Section 3.1 uses quantile regressions to demonstrate that lease expirations generate downside risk to property performance. Section 3.2 shows that the effects of expirations are amplified in markets with higher vacancy rates.

## 3.1 Quantile Regression Estimates

The effects of lease expirations on occupancy and income are likely to be asymmetric. The asymmetry is obvious regarding the occupancy rate, as occupancy would remain the same if the lease is renewed or the tenant replaced, but decline if the original tenant downsizes or completely vacates the property. Similarly, the increase in rent that could be achieved if a new lease is signed is likely much less than the loss in rent that would occur if a tenant departs.

To capture this asymmetry, we start by presenting quantile regression estimates of the relationship between property performance and lease expirations, controlling for the initial vacancy rate of the property.[8] The sample covers the years 2009 through 2018 in order to examine the effects of leases that expired before the pandemic.

Figure 1 plots estimates of how lease expirations affect various quantiles of occupancy changes (the left panel) and NOI growth (the right panel). The dashed line marks the OLS estimate from the same specification. This figure reveals that lease expirations typically do not affect occupancy or NOI notably. At the median and higher quantiles, more expirations are associated with no change in occupancy and only modest differences in NOI growth. This suggests that leases are typically renewed (or replacement tenants found quickly), and at rents comparable to those of existing leases. However, expirations present substantial downside risk. At the fifth percentile, the estimated elasticities are about $-0.4$ and $-0.25$ for occupancy and NOI growth, respectively, meaning that expirations lead to an increase in vacancy that is almost half the amount of space accounted for by the expiring leases.

A couple of factors likely contribute to lease expirations affecting performance predominantly at the lower quantiles. First, as already discussed, the effects of expirations are inherently asymmetric; if tenants depart, occupancy and income may fall sharply, whereas if they stay, the property's financials may change little. Thus, even if outcomes of lease ex-

[8] We exclude property type-year fixed effects in this specification because a greater response to lease expirations in times of stress is one factor that could cause effects to be asymmetric, but results are broadly similar when these fixed effects are included.

pirations are completely determined by idiosyncratic factors related to the tenants, it would be mostly the lower quantiles that are affected. Second, lease expirations are likely more detrimental in weaker markets, as tenants are harder to replace and equilibrium rents may have declined relative to other markets. Again, lease expirations would affect the bottom part of the distribution, but because the effects of expirations are most pronounced for properties that are already strained. We investigate this second mechanism next, showing that property performance indeed deteriorates more following lease expirations in markets with higher vacancy rates.

## 3.2 Role of Local Conditions

The effects of lease expirations should depend on local conditions. In a tighter market, it is harder to find alternative space, so tenants would be less likely to leave their current space and have less bargaining power in renewal negotiations. To study such effects, we now estimate equation (1) including interaction terms with the market-level vacancy, which is measured using the availability rate reported by CBRE for the given city, property type, and quarter as of the start of the financial-reporting window.[9]

Table 2 presents the coefficient estimates from this analysis. For comparison, the first column reports the baseline OLS estimates without the market-vacancy-related terms. It shows that a 10 percentage point increase in lease expirations results in a roughly 80 basis point decline in occupancy, on average. Column 2 interacts lease expirations with the market vacancy rate, thus allowing the effects of lease expirations to depend on market conditions. As expected, the adverse effects of expirations increase with the market vacancy rate; the estimates imply an elasticity of occupancy with respect to expirations of about $-0.06$ in markets with a 10 percent vacancy rate, compared with an elasticity of $-.03$ in a market with no vacancy. Column 3 presents quantile regression estimates of the effect of lease expirations on the 25th percentile of occupancy changes. The estimates indicate that the detrimental effects of lease expirations in weaker property markets are felt predominantly on the lower end of the performance distribution, similar to the pattern shown in Figure 1.

Columns 4 through 6 repeat this analysis for NOI growth. Overall, the effects of lease expirations on income growth are roughly similar to the effects on occupancy, but the importance of tightness in the local property markets is even more pronounced. In fact, when market vacancy is low, lease expirations are associated with modest increases in income. However, when the market vacancy rate is high, lease expirations are associated with greater declines, on average, in NOI than in occupancy. The estimates imply that lease expirations

[9]For properties in markets not covered by CBRE, We use the national index for the property type and quarter. Our estimates change little when we restrict the sample to properties in CBRE markets.

are neutral with respect to income growth when the market vacancy is about 3 percent, but the elasticity between NOI and the expiring-lease share moves to about −0.05 in a market with a 10 percent vacancy rate. Again, effects are stronger for lower quantiles, indicating that weaker market conditions amplify the downside risks stemming from lease expirations.

# 4 Effects of Lease Expirations During the Pandemic

The estimates reported in Section 3.2 demonstrate that the effects of lease expirations reflect the strength of the local property market. Motivated by this finding, we now analyze how the relationship between lease expirations and property performance changed during the COVID-19 pandemic. Section 4.1 reveals that the adverse effects of lease expirations on property performance increased during the pandemic, driven by office properties. Section 4.2 shows that these adverse effects have been concentrated in CBDs and areas where the shift to remote work has been more persistent.

## 4.1 Effects by Property Type

To investigate how the effect of lease expirations on property performance has changed since the COVID-19 outbreak, we extend the sample to include the pandemic era and add to the specification an extra variable, COVID Expirations$_{i,t,t+1}$, which is the interaction of the share of expiring leases with a pandemic indicator (equal to 1 if $t$ is 2020 or later).[10]

Table 3 presents the estimates from these regressions. Columns 1 through 4 report the effects on occupancy rate changes, while columns 5 through 8 report results for NOI growth. The OLS estimates presented in column 1 consider occupancy changes for the full sample of all property types for which leasing data are available. Overall, while lease expirations are associated with significant increases in vacancies (as found for the pre-COVID sample in Table 2), the effects of expirations became only slightly stronger during the pandemic, rising from 0.07 before to 0.09 during the pandemic.

One reason that the adverse effects of lease expirations may not appear to be greatly magnified during the pandemic is that the sample includes many properties with limited susceptibility to the disruptions associated with the crisis. For example, while the office sector has been significantly affected by the shift to remote work, as noted by Gupta et al. (2022), the acceleration in e-commerce sales during the pandemic boosted demand for industrial real

[10]When the lease-expiration window starts in 2019 but ends in 2020, we do not count it as a COVID expiration, as tenants could renew before becoming aware of the pandemic. We exclude these 2019 observations in our baseline specifications, but results are robust to either including them as pre-COVID expirations or to coding them as COVID expirations.

estate (such as warehouses). We thus next analyze the effects of pandemic lease expirations separately by property type. Columns 2 through 4 report these estimates, with the sample restricted to office, retail, and industrial properties, respectively.

As would be expected, the pandemic amplified the effects of lease expirations more for offices than for retail or industrial properties. The estimated elasticity between office occupancy growth and lease expirations rose in magnitude from $-0.09$ before to $-0.15$ during the pandemic (column 2). Likewise, the elasticity for NOI growth deteriorated from about $-0.14$ to $-0.27$ (column 6). Put differently, damage done by lease expirations rose by over one-half for office properties.

The other two commercial property types have fared better by comparison. For retail, the elasticities of occupancy and income vis-à-vis lease expirations were unchanged during the pandemic relative to the period before the outbreak (columns 3 and 6). Lease expirations actually became slightly less problematic for industrial properties during COVID-19, consistent with increased demand for these properties due to pandemic-induced shift in spending patterns (columns 4 and 8).

In addition to tenants becoming more likely to vacate their offices upon lease expiration, the estimates in Table 3 also indicate that vacant space has become more difficult to fill. The coefficient of 0.63 on Property Vacancy$_{i,t}$ indicates that landlords were able to fill about two-thirds of their vacant space during the financial-reporting window in the pre-pandemic period. However, this rate at which vacant space is filled fell by about half for office and retail properties during the pandemic. This means that, when tenants do leave, space is likely to remain vacant longer. We investigate the implications of this result for future vacancy rates in Section 5.1.

## 4.2 Effects of Office Lease Expirations by Geography

Since the effects of the COVID-19 pandemic are most pronounced for offices, the rest of the analysis focuses on the subsample of office properties. In particular, we explore whether offices in markets with a greater shift toward remote work exhibited greater vulnerability to lease expirations during the pandemic. We identify such vulnerable places using two metrics: being a central business district (CBD) or suffering a more persistent decline in time spent at workplaces (or equivalently, more remote work). We estimate equation (1) for office properties only, allowing the effects of lease expirations to depend on these geographic variables. The coefficients on these interaction terms measure cross-location heterogeneity in the adverse effects of lease expirations and how they changed during the pandemic.

Table 4 presents these estimates. For comparison, columns 1 and 4 repeat columns 2 and

5 of Table 3, respectively, estimating the effects of lease expirations on office performance without the geographic variables. Columns 2 and 5 add interactions between the expiration variables and an indicator for whether the property's ZIP code is in a CBD (according to CBRE submarket definitions). Columns 3 and 6 add further interactions with the decline in time spent at workplaces relative to before the pandemic to capture the shift toward remote work. Appendix Table B.1 presents quantile regression estimates of the same specification. As with the earlier results, the effects of lease expirations on the 25th percentile of occupancy or NOI growth are generally larger than the OLS estimates but exhibit similar cross-sectional patterns.

Columns 2 and 5 show that the adverse effects of lease expirations became much more pronounced for CBD properties during the COVID-19 pandemic. The marginal effect of lease expirations on occupancy during the pandemic was $-0.24$ for CBD properties, compared with about $-0.14$ for other office properties, and only $-0.09$ before the pandemic for all offices. That is, the detrimental effect of expirations on occupancy nearly tripled during the pandemic for CBD properties.

Patterns are broadly similar for income growth; the elasticity between NOI growth and lease expirations rose from about $-0.14$ to $-0.26$ for non-CBD properties during the pandemic, and from about $-0.16$ to $-0.48$ for CBD properties. These geographic differences are consistent with the findings from Ghosh et al. (2022) that, during the pandemic, property values for suburban office properties remained more resilient than valuations for urban offices.

Finally, columns 3 and 6 add interactions with the decline in time at workplaces. While more prevalent shifts to remote work are correlated with properties being located in a CBD, this variable also contains additional information relevant for the effects of lease expirations. Raising Work From Home$_{c(i)}$ by 0.15 (roughly the difference between New York City and the average property in the sample) increases the adverse effect of lease expirations on occupancy during the pandemic by about 0.06.[11] While this effect is economically meaningful, it is statistically insignificant due to the high correlation of remote work with the CBD indicator.[12]

A greater shift to remote work is also associated with deterioration in occupancy and income during COVID-19 even when leases are not expiring, but the effects are smaller. Overall, the results indicate that demand for office space fell in CBDs and localities with a greater shift to remote work. Lease expirations hasten the rate at which this fundamental

[11] Appendix Table B.2 shows that these findings are generally robust to alternative measures of work-from-home intensity, to be discussed further following Table 5.

[12] The correlation is 0.4 for the sample of office properties. When the CBD control is omitted, the coefficients on Work From Home$_{c(i)}$ are -0.51 and -1.0 in regressions predicting occupancy changes and NOI growth, respectively, and statistically significant.

decline in demand affects property performance, and thus are useful for revealing the magnitude of the shift. In addition, Appendix Figure B.2 shows that occupancy rates at the market level have declined in markets with a greater shift to remote work. In fact these declines were accelerating rather than moderating as of the end of 2023, indicating conditions are likely to continue to deteriorate for some time, a topic we discuss further in the next section.

Table 5 extends the analysis to consider additional factors that could interact with lease expirations during COVID-19. Gupta et al. (2022) show that leasing activity and rents fell more for lower-quality offices, consistent with a greater preference for higher-amenity space to attract workers back to the office. To proxy for such effects, we add interaction terms with $\text{Unrenovated}_{i,t_-}$ (an indicator equal to one if the property was last renovated more than 20 years ago), and with the (log) property price per square foot as of the last appraisal. Columns (2) and (5) show that higher quality properties (as measured by valuation or recency of renovation) have smaller declines in occupancy and income when leases expire. Furthermore, these effects are robust to the inclusion of CBSA-year fixed effects in columns (3) and (6). Table B.2 further shows that these findings are generally robust to alternative measures of work-from-home intensity based on the American Community Survey (ACS) data, and measures of remote work potential in a locality (based on job types and job listings) as estimated by Dingel and Neiman (2020) and Hansen et al. (2023).

Overall, the cross-sectional determinants of the sensitivity to lease expirations align well with popular perceptions of which office properties are most vulnerable to the disruptions wrought by the pandemic. Namely, tenants are most likely to exit upon lease expiration in areas exhibiting greater tendency to shift toward remote work (as represented by CBDs and counties with a larger decline in time at work places) and in lower-quality properties (as proxied by renovation timing and property valuation).

# 5 Further Implications for the CRE and Banking Sectors

This section investigates the implications of the above findings for the longer-run performance of office properties and CRE lenders. First, Section 5.1 presents a simple model of office occupancy dynamics, and uses the regression results to project future vacancy rates for urban and suburban markets under different scenarios for the normalization of office market conditions. Second, motivated by a significant projected rise in future vacancy rates for CBD office markets, Section 5.2 analyzes the exposure of different CRE lenders to these at-risk markets. We demonstrate that small and regional banks are generally less exposed to CBD office loans than larger banks and nonbank lenders. Although this benefit is partially offset by smaller banks financing relatively lower-quality offices, we nonetheless find that small and regional banks are less exposed than other lenders to the most-adversely affected office properties.

## 5.1 Vacancy Rate Projections

Table 4 showed that, during COVID-19, lease expirations were associated with larger declines in occupancy, and vacant space became slower to fill. These findings indicate that vacancy rates are likely to continue to rise as more leases roll over. The important question is: how much will vacancy rise and how long will it remain elevated? To address this question, we use the empirical estimates to calibrate a simple reduced-form model of occupancy dynamics. Previously estimated regression coefficients map directly into model parameters and help gauge how vacancy rates may evolve going forward.

There are three channels through which a building's occupancy can change: occupied space being vacated because the lease is expiring, occupied space being vacated for other reasons (e.g., from bankruptcies, good guy clauses, or buyouts), and vacant space getting filled. Suppose that the owner of a building $i$ is able to fill vacant space at rate $f_{i,t}$, experiences tenant exits following lease expiration at rate $\lambda_{i,t}$, and exits outside of expirations at rate $\delta_{i,t}$. Then the change in occupancy can be described by the following law of motion:

$$\Delta Occ_{i,t} = f_{i,t} Vac_{i,t} - \lambda_{i,t} Exp_{i,t} - \delta_{i,t}(1 - Vac_{i,t} - Exp_{i,t}) \tag{2}$$

Where $Occ_{i,t}$ and $Vac_{i,t}$ are the occupancy and vacancy rate, respectively, and $Exp_{i,t}$ is the share of space with expiring leases.

Then we can use the following regression

$$\Delta Occ_{i,t} = \alpha + \beta^{vac} Vac_{i,t} + \beta^{exp} Exp_{i,t} + \varepsilon$$

to back out the average filling rate and the two exit rates:

$$\begin{aligned} \delta &= -\alpha \\ f &= \beta^{vac} + \alpha \\ \lambda &= -(\beta^{exp} + \alpha) \end{aligned}$$

Likewise, by parameterizing the exit rate as $\lambda_{i,t} = \lambda_0 + \lambda_1 CBD_i + COVID_t(\lambda_2 + \lambda_3 CBD_i)$

(and parameterizing $f_{i,t}$ and $\delta_{i,t}$ analogously), we can use coefficient estimates from fully-interacted regressions along the lines of Equation 1 to back out how these parameters changed during COVID-19 for CBD and non-CBD properties.[13]

The primary value of this simple model is to provide a framework for assessing how the change in leasing dynamics during COVID-19 will affect future vacancy rates for office properties under alternative scenarios for the path of leasing dynamics. The results of this exercise are presented in Table 6. The estimates indicate that lease breaks (that is, exits outside of expirations) declined during COVID, perhaps owing to low levels of bankruptcies in 2021 and 2022. However, this effect was more than offset by a decline in the rate at which vacant space was filled ($f$) from 0.49 before the pandemic to 0.18 during the pandemic, and an increase in the rate at which tenants exit upon lease expiration ($\lambda$) from 0.16 to 0.18. These last two effects are more pronounced for offices in CBDs (columns 5 and 6) than for suburban offices (columns 3 and 4).

Roughly 10% of leases expire per year in the data, namely $\mathbb{E}(Exp_{i,t}) = 0.10$. Treating this rate as exogenous and assuming it will remain roughly the same going forward, we can use equation (2) to solve for the vacancy rate in steady state (that is, the vacancy rate such that $\mathbb{E}(\Delta Occ_{i,t}) = 0$) as:

$$Vac^{SS}_{i,t} = \frac{\hat{\delta}_{i,t} + (\hat{\lambda}_{i,t} - \hat{\delta}_{i,t}) \times 0.11}{\hat{f}_{i,t} + \hat{\delta}_{i,t}}$$

These implied steady-state vacancy rates are reported in the last row of Table 6. Before the pandemic, leasing dynamics—embodied in the exit rates and filling rate—were consistent with a steady-state vacancy rate of 13.5%. The COVID-period estimates provide the vacancy rate at which a market would stabilize under the extreme assumption that the leasing dynamics observed during the first couple of years of the pandemic were to become permanent. These estimates indicate that office vacancy would rise to about 20% in suburban office markets and 40% in CBD office markets.

The actual rise in longer-term vacancy rates will presumably be much smaller, as a few factors should push $f$ up and $\lambda$ down over time. First, those tenants with the greatest propensity to switch to a remote-work-heavy model will constitute a diminishing share of the tenant pool over time as leases expire, leaving the composition of tenants tilted more toward those who are willing to maintain their office space. In other words, those tenants who have chosen to sign new leases during the pandemic are likely to exit at a slower rate than the overall pool of tenants who entered into leases before the pandemic. This would tend to push $\lambda$ back toward pre-pandemic levels over time. Second, in the longer run, supply

[13] To focus on the effects of lease expirations, the specifications in Table 4 did not interact the vacancy rate with the geographic risk factors, so they differ slightly from the specification in this section.

should be able to adjust to the lower demand through lower rates of construction and the conversion of offices to other property types. This would reduce the excess supply of office space and make vacant space easier to fill. Third, over time, landlords are likely to reduce asking rents more in an effort to clear the market. This process may be aided by the turnover of owners for distressed properties, as the lower prices paid by the new owners would enable them to profitably lease space at lower rents.

To investigate how vacancy would evolve under different scenarios for the speed at which leasing dynamics improve, Figure 2 projects changes in vacancy rates for CBD and suburban office markets under three different scenarios. First, the top of the shaded region marks the projected change in vacancy rates if the COVID-era dynamics were to remain permanent. Second, the bottom of the shaded region corresponds to the most optimistic scenario where leasing dynamics revert fully to the pre-pandemic parameters (those from columns 3 and 5 of Table 6) starting in 2024. Finally, the dashed line shows the intermediate projection if $f$, $\lambda$ and $\delta$ revert back to pre-pandemic values starting in 2024 at a geometric rate of 2.5 percent per quarter (roughly the rate at which leases expire and loans mature). Each projection assumes that vacancy rates start at the pre-pandemic steady state, and projects changes in vacancy into the future using the particular sequence of $\{f_t, \lambda_t, \delta_t\}$ determined by the values in Table 6, along with the assumption for the rate at which conditions normalize after the sample period ends.

The projections show that the predicted rise in vacancy is particularly stark for CBD offices (in red), and the rate at which leasing conditions normalize are especially important. The projections predict about an 8-percentage-point increase in CBD vacancy rates over the first four years of the pandemic. Under the intermediate case with geometric reversion of leasing parameters going forward, CBD vacancy peaks in 2027 at around 10 percentage points above pre-pandemic levels, and then slowly returns to normal over the 2030s. However, because of large deterioration in leasing activity during the pandemic, there is a rather wide range of future outcomes depending on how quickly conditions normalize. For suburban markets (in blue), the deterioration to date in leasing activity is less stark, so the range of predicted outcomes is much smaller. Under the intermediate scenario, projected vacancy rates are only slightly below their peak as of the start of 2024, although they are expected to remain elevated for a while relative to before the pandemic.

How well do these projections line up with observed changes in vacancy rates? The solid lines plot the actual change in vacancy rates for CBD and suburban offices based on CBRE vacancy data.[14] The projections over the sample period, which act as an informal

[14]Estimates are formed by aggregating quarterly CBRE submarket vacancy rates by CBD and non-CBD markets, weighted by net rentable area. To align with the vacancy concept in the CMBS data, vacancy is

back-test of the model, match the observed change in vacancy rates for CBD markets, with both rising about 7.5 percent through the fourth quarter of 2023. However, the model under-predicts the actual rise in vacancy for suburban markets; vacancy rose by about 4 percentage points through 2023Q4 in suburban markets, but was projected to rise by only a bit over 3 percentage points. This indicates that the deterioration in suburban office markets might be slightly worse than indicated by the CMBS data, perhaps because CMBS loans tend to fund higher quality properties. On the other hand, the difference is fairly modest. This small discrepancy notwithstanding, our estimates indicate that CBD markets have experienced more deterioration to date, and face a murkier outlook for the future.

## 5.2 Exposures of Lenders to At-risk Office Markets

The results so far demonstrate that the effects of the COVID-19 pandemic on the office CRE sector are far from uniform. In areas outside of CBDs and where the amount of time spent at workplaces has not declined notably since the start of the pandemic, leasing dynamics do not differ substantially relative to before the pandemic. That is, when leases expire, the spaces continue to be filled at rates and rents similar to those observed over the decade before the COVID-19 outbreak. However, in CBDs and markets where remote work has risen notably, lease expirations have proven more damaging to occupancy and income. This corroborates the narrative that demand for office space in those markets has fundamentally weakened, causing property performance to deteriorate as leases roll over. Because the various types of CRE lenders differ in their geographic footprint, these cross-market differences have potentially important implications for which lenders are most exposed to losses from office loans in the coming years.

The left panel of Figure 3 plots the share of outstanding office loans made by G-SIB and foreign banks, nonbank CRE lenders (for example, CMBS and life insurers), and smaller domestic banks that are secured by properties with the following risk factors: central business district locations (red bars), counties with an over-one-third decline in time at workplaces (blue bars), year of last renovation before 2000 (purple bars), and a price per square foot under $300. The sample includes office properties in RCA's database, which covers CRE properties valued at more than $2.5 million. Because offices in central business districts are more likely to meet this reporting threshold, the estimated exposure to at-risk markets is likely biased upward, especially for smaller banks, which tend to make smaller loans. Outstanding loans are not directly reported, but are imputed based on the absence of subsequent transactions and on origination and maturity dates.[15]

measured as "direct vacancy," which excludes space available for sublease.

[15] We impute a loan to be outstanding if (1) there are no future transactions associated with the property,

The figure shows that small and regional domestic banks tend to finance properties located in markets less exposed to the COVID-19-related disruptions. Nearly half of office CRE loans from G-SIB or foreign banks and nonbanks are in CBDs, and slightly more than 40 percent are in counties with a high work-from-home share. In contrast, only about 20 percent of the office loan portfolios of smaller domestic banks are subject to these risk factors.

While smaller banks tend to originate office loans in less adversely-affected markets, their loans have other risk factors. About half of office loans from smaller banks are secured by properties that have not been renovated since before 2000 (compared to about one-third of loans for other lenders), and bank-funded offices tend to have lower valuations. Consequently, loans from smaller domestic banks might be hurt more by the flight-to-quality effects documented in Table 5.

To understand how these potentially offsetting effects net out, we use the coefficient estimates from column (2) of Table 5 to estimate the average elasticity of occupancy with respect to lease expirations for the loans of different types of CRE lenders. These estimates measure the rate at which tenants leave as leases expire and thus is an indicator of the degree of stress for a lender's office loan portfolio given its characteristics. The right panel of Figure 3 plots kernel density estimates of the distribution of elasticities for the three lender categories. The distribution for smaller domestic banks (the blue line) is clearly located to the right of those for the other lender groups, indicating a smaller tendency for tenants to vacate upon lease expiration. On average, smaller domestic banks have an elasticity of -0.19, while non-banks and larger banks have elasticities of -0.20 and -0.21, respectively.

The comparatively lower exposure of smaller banks to the most at-risk loans is primarily driven by these banks making smaller loans, which tend to finance properties located in the parts of cities facing less of a decline in office demand. Specifically, Appendix Table C.1 investigates the determinants of smaller banks' market shares for office loans. The results confirm that (1) smaller banks made fewer office loans in CBDs and counties with more working from home, (2) these differences predominantly reflect where small banks originate loans *within cities*, and (3) these differences are mostly explained by difference in loan sizes.[16]

In sum, while there remains some concern about small and regional banks facing headwinds from high CRE loan concentrations and funding pressures, these banks appear to be at least partially protected from loan losses by having most of their office loans in CRE mar-

or future transactions involve the assumption of existing debt, and (2) its maturity date is beyond April 2023. If a maturity date is not reported, it is imputed by assuming the loan has a ten year term, the most prevalent maturity in the sample.

[16]Note that this pattern of properties outside of CBDs securing smaller loans is based on the loans recorded in the RCA data, which exclude properties valued at less than $2.5 million. This exclusion implies that smaller banks' true exposure to CBDs should be even lower than estimated here because more of their loans are secured by properties below this reporting threshold and thus even less likely to be in a CBD.

kets less damaged by the pandemic. Between this more favorable geographic distribution of lending and a superior ability to renegotiate CRE loans to avoid foreclosures (Black et al., 2020; Glancy et al., 2022), small and regional banks may be better positioned than other lenders to weather the strains in the office sector.

# 6 Conclusion

This paper documents three key facts about the relationship between lease expirations and CRE property performance. First, lease expirations create notable downside risk for the performance of commercial properties. While the intensity of lease expirations has little effect on median or better financial performance, it significantly impacts the lower end of the distribution. Specifically, lease expirations increase the likelihood that a property experiences a large decline in occupancy and income.

Second, this risk of performance deterioration following lease expirations is highly sensitive to the strength of the local property market. In markets with low vacancy rates, lease expirations have little effect on a property's occupancy and are associated with modest increases in income. Put differently, in tight markets, commercial spaces with expiring leases reliably see their leases renewed or replaced, and often at a higher rent than that of existing leases. However, in markets with high vacancy rates, occupancy and income fall notably when leases expire.

Third, while the CRE market as a whole has remained relatively resilient since the COVID-19 outbreak, there are segments for which lease expiration outcomes point toward serious stresses. The adverse effects of lease expirations on the financial performance of office buildings increased notably during the pandemic, especially for properties in central business districts or counties with a persistently larger shift to remote work.

The CRE market also faces headwinds besides those from the enduring shift toward remote work. Higher interest rates raise debt service costs and reduce property values. Additionally, more restrictive loan underwriting may amplify difficulties refinancing maturing loans. To the extent that realized or anticipated loan losses cause banks to tighten credit conditions more generally, these developments may also feed back into the broader economy (see, for example, Peek and Rosengren, 2000). This risk is somewhat mitigated by the fact that office loans generally constitute a modest portion of smaller banks' CRE portfolios, and those loans are predominantly in less adversely affected markets. Nevertheless, there are still some banks for which CRE may pose more of a threat to capital adequacy, namely those with a greater concentration in at-risk loans, or those so concentrated in CRE that even moderate losses would strain capital. This may in turn constrain credit availability for some bank borrowers going forward.

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Table 1: Summary Statistics

| Variable | Mean | sd | Percentile | | | N |
|---|---|---|---|---|---|---|
| | | | 25 | 50 | 75 | |
| $\text{Expirations}_{i,t,t+1}$ | 0.101 | 0.173 | 0.000 | 0.020 | 0.135 | 116,924 |
| $\Delta\text{Occupancy}_{i,t_-}$ | -0.005 | 0.176 | -0.010 | 0.000 | 0.007 | 116,924 |
| $\text{NOI Growth}_{i,t_-}$ | 0.020 | 0.267 | -0.074 | 0.011 | 0.100 | 116,924 |
| $\text{Property Vacancy}_{i,t_-}$ | 0.083 | 0.155 | 0.000 | 0.010 | 0.110 | 116,924 |
| $\text{Market Vacancy}_{m(i),t_-}$ | 0.137 | 0.054 | 0.095 | 0.126 | 0.175 | 116,924 |
| $\text{Central Business District}_{z(i)}$ | 0.060 | 0.237 | 0.000 | 0.000 | 0.000 | 116,924 |
| $\text{Work From Home}_{c(i)}$ | 0.244 | 0.071 | 0.212 | 0.254 | 0.293 | 116,924 |
| $\text{Unrenovated}_{i,t_-}$ | 0.301 | 0.459 | 0.000 | 0.000 | 1.000 | 115,977 |
| $\ln(\text{Price Per Sq Ft})_{i,t_-}$ | 5.209 | 0.723 | 4.761 | 5.203 | 5.671 | 108,915 |
| $\text{COVID}_t$ | 0.183 | 0.387 | 0.000 | 0.000 | 0.000 | 116,924 |
| $\text{Office}_i$ | 0.285 | 0.451 | 0.000 | 0.000 | 1.000 | 116,924 |
| $\text{Retail}_i$ | 0.606 | 0.489 | 0.000 | 1.000 | 1.000 | 116,924 |
| $\text{Industrial}_i$ | 0.109 | 0.312 | 0.000 | 0.000 | 0.000 | 116,924 |

*Notes:* Summary statistics for regression sample. $i$ indexes properties, and $t$ denotes the start of the one-year lease expiration window under consideration. Market vacancy rates and CBD definitions come from CBRE, and the county-level decline in time at workplaces (Work From Home) are from Google mobility data (via Opportunity Insights). Remaining variables come from Morningstar CMBS data. Unrenovated is an indicator for whether the most recent renovation was over 20 years ago, and Price Per Sq Ft is the ratio of the value of the most recent appraisal to the property square footage. NOI Growth and Price Per Sq Ft are winsorized at the 1 percent level.

Table 2: Heterogeneous Effects by Market Vacancy

| | $\Delta$Occupancy$_{i,t_-}$ | | $Q_{25}(\Delta \text{Occ}_{i,t_-})$ | NOI Growth$_{i,t_-}$ | | $Q_{25}(\text{NOI Gr}_{i,t_-})$ |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Expirations$_{i,t,t+1}$ | -0.08** | -0.03* | 0.02$^+$ | -0.09** | 0.03$^+$ | -0.00 |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) |
| Property Vacancy$_{i,t_-}$ | 0.64** | 0.64** | 0.02** | 0.08** | 0.08** | -0.20** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Market Vacancy$_{m(i),t_-}$ | | -0.24** | 0.00 | | -0.32** | -0.26** |
| | | (0.02) | (0.00) | | (0.04) | (0.03) |
| $\times$ Expirations$_{i,t,t+1}$ | | -0.33** | -1.35** | | -0.84** | -1.18** |
| | | (0.08) | (0.10) | | (0.11) | (0.13) |
| $R^2_a$ | 0.315 | 0.317 | | 0.013 | 0.015 | |
| $R^2_a$(within) | 0.313 | 0.315 | | 0.006 | 0.009 | |
| Observations | 96,064 | 96,064 | 96,064 | 96,064 | 96,064 | 96,064 |
| Property Type-Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Notes:* The dependent variable is the change in occupancy (columns 1 through 3) or NOI growth (columns 4 through 6). Columns 3 and 6 present estimates from quantile regressions (25th quantile), while the other columns present OLS estimates. Market Vacancy$_{m(i),t_-}$ denotes the vacancy rate in property $i$'s market as defined by CBRE. "$\times$Expirations$_{i,t,t+1}$" denotes its interaction with Expirations$_{i,t,t+1}$. Standard errors, in parentheses, are clustered by loan. $^+$,$^*$,$^{**}$ indicate significance at 10%, 5%, and 1%, respectively.
*Sources:* Morningstar, CBRE, and authors' calculations.

Table 3: Effects of Lease Expirations during the Pandemic

| | $\Delta$Occupancy$_{i,t_-}$ | | | | NOI Growth$_{i,t_-}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | Full Sample | Offices | Retail | Industrial | Full Sample | Offices | Retail | Industrial |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Expirations$_{i,t,t+1}$ | -0.07** | -0.09** | -0.07** | -0.05** | -0.09** | -0.14** | -0.06** | -0.09** |
| | (0.00) | (0.01) | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| COVID Expirations$_{i,t,t+1}$ | -0.02* | -0.06** | -0.00 | 0.02 | -0.06** | -0.13** | -0.01 | 0.01 |
| | (0.01) | (0.02) | (0.01) | (0.01) | (0.02) | (0.04) | (0.02) | (0.03) |
| Property Vacancy$_{i,t_-}$ | 0.63** | 0.55** | 0.69** | 0.57** | 0.07** | 0.05* | 0.07** | 0.17** |
| | (0.01) | (0.01) | (0.01) | (0.06) | (0.01) | (0.02) | (0.01) | (0.04) |
| $\times$ COVID$_t$ | -0.30** | -0.34** | -0.29** | 0.04 | -0.04 | -0.18** | 0.02 | 0.63** |
| | (0.02) | (0.02) | (0.02) | (0.07) | (0.04) | (0.07) | (0.05) | (0.14) |
| $R_a^2$ | 0.295 | 0.220 | 0.351 | 0.243 | 0.018 | 0.016 | 0.014 | 0.039 |
| $R_a^2$(within) | 0.291 | 0.218 | 0.349 | 0.238 | 0.006 | 0.011 | 0.003 | 0.019 |
| Observations | 125,247 | 35,563 | 75,882 | 13,802 | 125,247 | 35,563 | 75,882 | 13,802 |
| Property Type-Year FEs | ✓ | | | | ✓ | | | |
| Year FEs | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ |

*Notes:* This table presents estimates of the effects of lease expirations on occupancy (columns 1 through 4) and NOI growth (columns 5 through 8). Expirations$_{i,t,t+1}$ is the share of leases (in terms of square footage) set to expire, and COVID Expirations$_{t,t+1}$ denotes its interaction with an indicator for whether $t$ is 2020 or later. For each outcome variable, the first column presents estimates for the full sample of properties, and the next three restrict the sample to office, retail, and industrial properties, respectively. All specifications control for the property's initial vacancy rate and its interaction with the COVID indicator, and include either property type-year (the first column in each block) or year fixed effects (the other columns). Standard errors, in parentheses, are clustered by loan. $^{+,*,**}$ indicate significance at 10%, 5%, and 1%, respectively.
*Sources:* Morningstar and authors' calculations.

Table 4: Effects of Office Lease Expirations during the Pandemic, Geographic Differences

| | $\Delta$Occupancy$_{i,t_-}$ | | | NOI Growth$_{t,t_-}$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Expirations$_{i,t,t+1}$ | -0.09** | -0.09** | -0.08* | -0.14** | -0.14** | -0.01 |
| | (0.01) | (0.01) | (0.03) | (0.01) | (0.01) | (0.05) |
| × Central Business District$_{z(i)}$ | | 0.00 | 0.01 | | -0.02 | 0.01 |
| | | (0.02) | (0.03) | | (0.04) | (0.04) |
| × Work From Home$_{c(i)}$ | | | -0.07 | | | -0.50** |
| | | | (0.12) | | | (0.19) |
| COVID Expirations$_{i,t,t+1}$ | -0.06** | -0.05* | 0.05 | -0.13** | -0.12** | 0.09 |
| | (0.02) | (0.02) | (0.06) | (0.04) | (0.04) | (0.11) |
| × Central Business District$_{z(i)}$ | | -0.10* | -0.07 | | -0.20$^+$ | -0.14 |
| | | (0.05) | (0.06) | | (0.10) | (0.11) |
| × Work From Home$_{c(i)}$ | | | -0.37 | | | -0.79$^+$ |
| | | | (0.24) | | | (0.43) |
| COVID$_t$ | | | | | | |
| × Property Vacancy$_{i,t_-}$ | -0.34** | -0.34** | -0.34** | -0.18** | -0.18** | -0.18** |
| | (0.02) | (0.02) | (0.02) | (0.07) | (0.07) | (0.07) |
| × Central Business District$_{z(i)}$ | | -0.01* | -0.00 | | -0.02 | 0.00 |
| | | (0.01) | (0.01) | | (0.02) | (0.02) |
| × Work From Home$_{c(i)}$ | | | -0.17** | | | -0.30** |
| | | | (0.04) | | | (0.08) |
| Property Vacancy$_{i,t_-}$ | 0.55** | 0.55** | 0.55** | 0.05* | 0.05* | 0.05* |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.02) |
| Central Business District$_{z(i)}$ | | -0.00 | -0.01 | | 0.02* | -0.00 |
| | | (0.00) | (0.00) | | (0.01) | (0.01) |
| Work From Home$_{c(i)}$ | | | 0.05$^+$ | | | 0.25** |
| | | | (0.03) | | | (0.04) |
| $R^2_a$ | 0.220 | 0.221 | 0.222 | 0.016 | 0.016 | 0.018 |
| $R^2_a$(within) | 0.218 | 0.219 | 0.220 | 0.011 | 0.012 | 0.013 |
| Observations | 35,482 | 35,482 | 35,482 | 35,482 | 35,482 | 35,482 |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table presents estimates of the effects of lease expirations on occupancy and income growth for office properties. Expirations$_{i,t,t+1}$ is the share of leases (in terms of square footage) set to expire in the financial financial reporting window, and COVID Expirations$_{i,t,t+1}$ interacts this expiration share with an indicator for whether $t$ is 2020 or later. The dependent variable is the change in occupancy in columns 1 through 3 and the growth in NOI in columns 4 through 6. Columns 1 and 4 repeat results from Table 3, columns 2 and 5 add interactions for whether the property is in a central business district, and columns 3 and 6 add interactions for the percentage decline in time spent at workplaces relative to pre-pandemic levels. All specifications control for the initial vacancy rate, its interaction with the COVID-19 indicator, and year fixed effects. Standard errors, in parentheses, are clustered by loan. $^{+},^{*},^{**}$ indicate significance at 10%, 5%, and 1%, respectively.
*Sources*: Morningstar, CBRE, Opportunity Insights, and authors' calculations.

Table 5: Effects of Office Lease Expirations during the Pandemic, Flight to Quality

| | $\Delta$Occupancy$_{i,t_-}$ | | | NOI Growth$_{i,t_-}$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Expirations$_{i,t,t+1}$ | -0.08* | 0.02 | 0.00 | -0.01 | 0.09 | 0.02 |
| | (0.03) | (0.08) | (0.09) | (0.05) | (0.14) | (0.14) |
| × Central Business District$_{z(i)}$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 |
| | (0.03) | (0.03) | (0.03) | (0.04) | (0.04) | (0.04) |
| × Work From Home$_{c(i)}$ | -0.07 | -0.05 | 0.02 | -0.50** | -0.44* | -0.40$^+$ |
| | (0.12) | (0.13) | (0.16) | (0.19) | (0.20) | (0.23) |
| × Unrenovated$_{i,t_-}$ | | 0.04* | 0.04* | | -0.01 | -0.01 |
| | | (0.02) | (0.02) | | (0.03) | (0.03) |
| × ln(Price Per Sq Ft)$_{i,t_-}$ | | -0.02 | -0.02 | | -0.02 | -0.01 |
| | | (0.02) | (0.02) | | (0.03) | (0.03) |
| COVID Expirations$_{i,t,t+1}$ | 0.05 | -0.24 | -0.21 | 0.09 | -0.61* | -0.52$^+$ |
| | (0.06) | (0.15) | (0.16) | (0.11) | (0.26) | (0.28) |
| × Central Business District$_{z(i)}$ | -0.07 | -0.09 | -0.10$^+$ | -0.14 | -0.16 | -0.19$^+$ |
| | (0.06) | (0.05) | (0.06) | (0.11) | (0.11) | (0.11) |
| × Work From Home$_{c(i)}$ | -0.37 | -0.48* | -0.45 | -0.79$^+$ | -1.16** | -0.79 |
| | (0.24) | (0.23) | (0.28) | (0.43) | (0.41) | (0.49) |
| × Unrenovated$_{i,t_-}$ | | -0.10** | -0.11** | | -0.04 | -0.07 |
| | | (0.04) | (0.04) | | (0.06) | (0.07) |
| × ln(Price Per Sq Ft)$_{i,t_-}$ | | 0.06* | 0.06* | | 0.15** | 0.11* |
| | | (0.03) | (0.03) | | (0.05) | (0.05) |
| $R^2_a$ | 0.222 | 0.217 | 0.225 | 0.018 | 0.021 | 0.031 |
| $R^2_a$(within) | 0.220 | 0.214 | 0.221 | 0.013 | 0.017 | 0.017 |
| Observations | 35,482 | 32,822 | 31,845 | 35,482 | 32,822 | 31,845 |
| Non-expiration-interacted controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | | ✓ | ✓ | |
| CBSA-Year FEs | | | ✓ | | | ✓ |

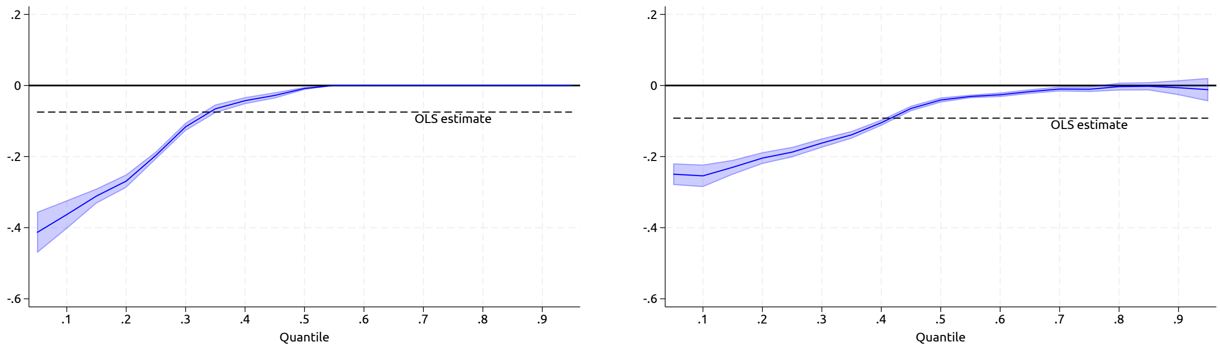
*Notes:* This table presents estimates along the lines of Columns (3) and (6) of Table 3, but adding interaction effects pertaining to building quality: Unrenovated$_{i,t_-}$ is an indicator for whether the years of construction and last renovation precede 2000, and ln(Price Per Sq Ft)$_{i,t_-}$ is the logarithm of the price per square foot of the property as of the most recent appraisal. Columns (1) and (4) repeat analysis from Table 3, Columns (2) and (5) add the new interaction terms to the specification, and columns (3) and (6) add CBSA-Year fixed effects. The four risk factors and their interaction with COVID$_t$ are included in the specification, but estimates are not displayed. Standard errors, in parentheses, are clustered by loan. $^{+,*,**}$ indicate significance at 10%, 5%, and 1%, respectively.
*Sources*: Morningstar, CBRE, Opportunity Insights, and authors' calculations.

Table 6: Estimates of Structural Parameters

| Market | Overall | | Suburban | | CBD | |
|---|---|---|---|---|---|---|
| Period | Pre-COVID | COVID | Pre-COVID | COVID | Pre-COVID | COVID |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\delta$ | 0.065 | 0.033 | 0.063 | 0.031 | 0.076 | 0.043 |
| | (0.001) | (0.003) | (0.001) | (0.003) | (0.003) | (0.007) |
| $f$ | 0.487 | 0.177 | 0.476 | 0.193 | 0.552 | 0.120 |
| | (0.005) | (0.014) | (0.006) | (0.016) | (0.014) | (0.039) |
| $\lambda$ | 0.160 | 0.184 | 0.159 | 0.175 | 0.168 | 0.279 |
| | (0.005) | (0.010) | (0.005) | (0.010) | (0.015) | (0.031) |
| Steady State Vacancy (%) | 13.5 | 23.0 | 13.5 | 20.2 | 13.6 | 40.9 |

*Notes:* This table presents estimates of the structural parameters affecting occupancy based on regressions of changes in occupancy on the property-level vacancy rate, the lease expiration share, and the interaction of these two variables with a COVID indicator (columns 1–2), or fully interacted with the COVID indicator, the CBD share, and their interaction (Columns 3–6). Columns (1) and (2) present estimates for dynamics before and during COVID, respectively, pooling across markets. Columns (3) and (4) present equivalent estimates for suburban office properties, and columns (5) and (6) for CBD office properties. The steady-state vacancy rate implied by the estimates is reported in the last row.

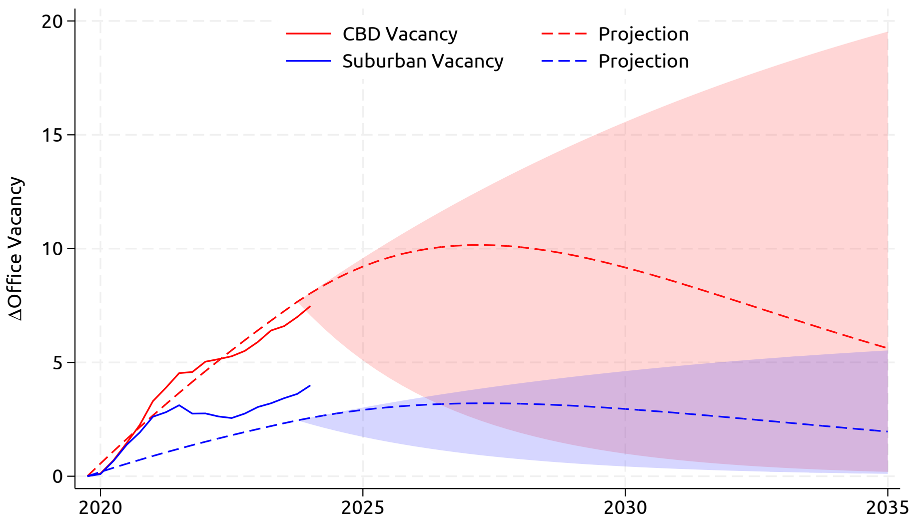
Figure 1: Effects of Lease Expirations from Quantile Regressions




(a) $\Delta$Occupancy$_{i,t-}$ (b) NOI Growth$_{i,t-}$

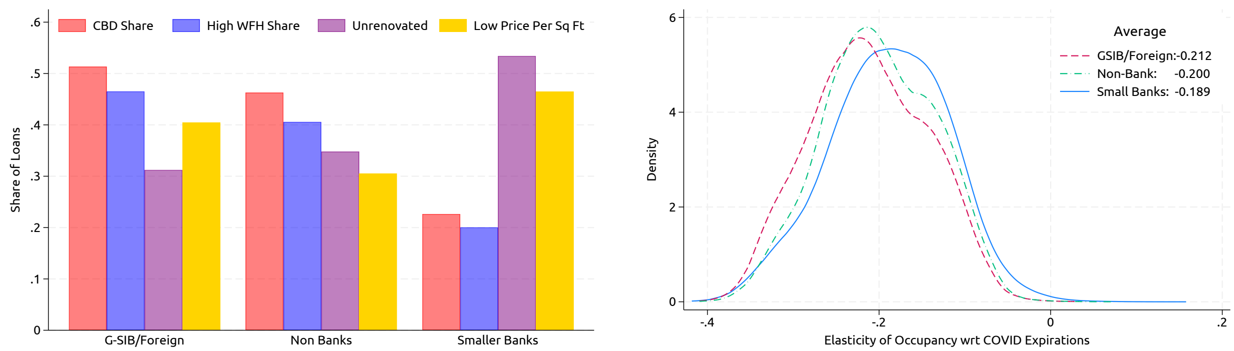
*Notes:* This figure plots quantile regression estimates of the effects of lease expirations on occupancy rate changes (left panel) and NOI growth (right panel) according to equation (1). The x-axis indexes the quantiles of each outcome variable, and the y-axis displays the coefficient estimate for a given quantile. The blue area represents the 95 percent confidence interval. Standard errors are clustered by loan.
*Sources:* Morningstar, and authors' calculations.

Figure 2: Changes in U.S. Office Vacancy




*Notes:* This figure plots projected changes in office vacancy rates for suburban (blue) and CBD (red) markets. Solid lines show observed changes in vacancy since 2019:Q4 based on CBRE data. The dashed line shows the projected changes in vacancy assuming markets start at their pre-COVID steady state, evolve according to the COVID-era parameter estimates from Table 6 for four years, and then have leasing parameters decay to pre-COVID levels at a rate of 2.5 percent per quarter. The shaded areas give the range of projected vacancy rates from the scenario where COVID-era parameters are permanent (the top of the range) to the one where they revert immediate to pre-COVID values after four years (the bottom of the range). Projections assume that 10% of leased space expires per year.
*Sources*: CBRE, and authors' calculations.

Figure 3: Exposures to At-risk Office Loans by Lender




(a) Specific Risk Factors

(b) Estimated Sensitivity to Expirations

*Notes:* The left figure plots the shares of lending in the RCA database that are secured by properties in central business districts (red bars), in counties where the time at workplaces declined by at least one-third relative to before the pandemic (blue bars), built and last renovated before 2000 (purple bars) and with a Price Per Square Foot under $300 (yellow bars). These shares are plotted for three lender groups: G-SIB/foreign banks, nonbanks, and smaller banks. The right figure plots a kernel density estimate of the average estimated elasticity of occupancy with respect to COVID lease expirations for the portfolios of the three lenders (based on the estimates reported in Column (2) of Table 5).

*Sources*: Morningstar, CBRE, Real Capital Analytics, Opportunity Insights, and authors' calculations.

# APPENDIX

## A Variable Construction

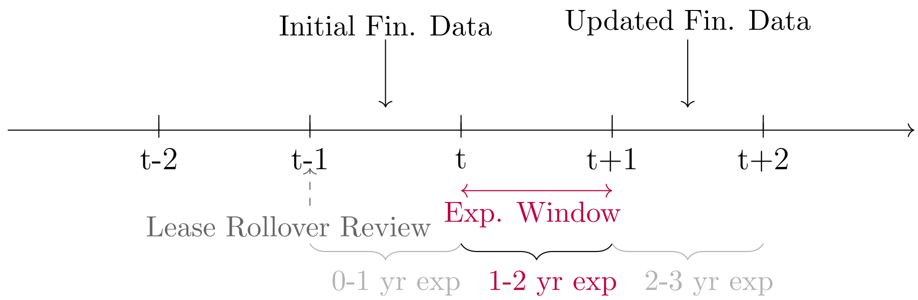
While data on the loans underlying commercial mortgage-backed securities (CMBS) deals are reported monthly, the variables concerning property performance and lease expiration schedules are updated less frequently. This appendix outlines how we address these timing issues. Figure A.1 displays a timeline for key variables pertaining to financial updates and lease expirations.

The primary explanatory variable is the share of leases (weighted by a tenant's square footage) expiring in a given year. CMBS data report lease expirations over separate one year intervals: For each lease rollover review, the shares of space with leases expiring within one year, one to two years, two to three years, three to four years, or more than four years are reported (the brackets in Figure A.1). We use scheduled lease expirations as measured one year before to avoid selection bias from early renewals, so our measure of lease expirations between $t$ and $t+1$ pertains to the lease rollover review as of $t-1$.[17]

For the performance variables (occupancy rate and net operating income), we consider changes over the shortest available time horizon that contains the lease expiration window. If a property reports financials annually, and financial reporting occurs halfway between rollover reviews (the circumstance depicted in the figure), then the outcome variables would be the change in the two years starting 6 months before the start of the lease expiration window and ending 6 months after the end of the window. These two dates are shown as "Initial Fin. Data" and "Updated Fin. Data" in Figure A.1. The actual lead and lag may differ depending on the timing of data reporting. We drop observations where the financial update is more than 1.5 years after the end of the lease expiration window in order to guarantee that we are consistently examining the near-term effects of expirations.

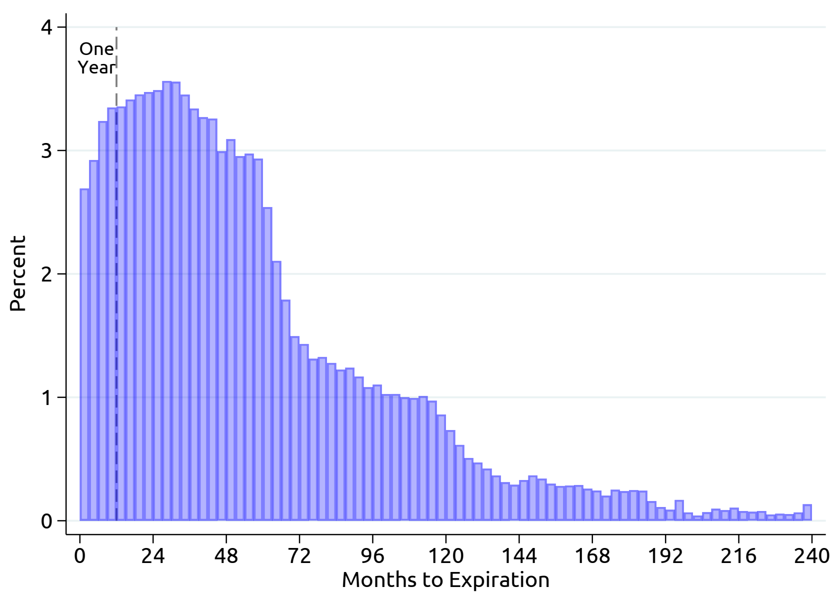
[17] Figure A.2, which plots the distribution of scheduled lease expirations as of 2019, shows that the density of scheduled lease expirations decreases in the three quarters before expiration (consistent with extensions being executed) but levels off at about a year out.

Figure A.1: Timeline of Lease Review and Lease Performance Reporting




*Notes*: This diagram illustrates the timing with which lease expirations and financial data are reported. "Lease Rollover Review" is the time lease data is reported, "Exp. Window" is the period over which lease expirations are measured, and "Initial Fin. Data" and "Updated Fin. Data" give the time points over which changes in occupancy or NOI growth are calculated. See Appendix A for detailed explanations.

Figure A.2: Distribution of Scheduled Lease Expirations as of 2019




*Notes:* This figure shows the distribution of the number of months to expiration for leases observed in 2019. It shows the distribution for properties' top five tenants by square footage of occupancy. (The exact expiration dates for these tenants are reported rather than just the aggregate expirations within a given window.)
*Sources:* Morningstar and authors' calculations.

# B Pandemic Risk Factors by Geography: Additional Results

This subsection presents three additional sets of results pertaining to geographic determinants of leasing dynamics, paying special attention to the change since the onset of COVID-19. First, we present quantile regression estimates demonstrating that the adverse effects of lease expirations in at-risk office markets (CBDs and counties with a larger shift to remote work) are particularly pronounced at lower quantiles. Second, we present results using alternative measures to quantify the shift to remote work. Third, we provide additional analysis on the effect the shift to remote work has had on market-level office occupancy.

Table B.1 presents quantile regression estimates of the form presented in Table 4. The results confirm that lease expirations during the pandemic had more severe effects on occupancy and net operating income (NOI) for offices in CBDs or counties with more remote work. Declines in occupancy and income following leases expirations in these more at-risk markets are stronger at the 25th percentile than in the OLS estimates, further demonstrating that lease expirations substantially increase the downside risk to property performance.

Table B.2 repeats the analysis in Table 5 for alternative measures of remote work intensity. Columns (1) and (5) repeat findings based on Google Mobility data, columns (2) and (6) measure the Work From Home share based on 2022 ACS data, columns (3) and (7) use the the share of jobs in a city that can be done remotely as measured by Dingel and Neiman (2020), and columns (4) and (8) use the share of 2022 and 2023 job postings in a city that allow for remote work from Hansen et al. (2023). Each measure of work from home is associated with greater adverse effects of lease expirations during COVID, as well as greater general declines in occupancy and NOI during COVID. Effects are generally a bit stronger for the Google-based work from home measure, perhaps because it has less sampling error than the ACS measure and is based on actual work from home rather than potential work from home as is the case with Dingel and Neiman (2020) and Hansen et al. (2023). However, estimates are reasonably similar in magnitude across these four measures.

Figure B.1 presents a scatter plot of availability rates against vacancy rates for CBRE markets. Blue dots present measures for 2019:Q4 and red for 2023:Q4. The figure shows that there is a tight linear relationship between the two measures, and that there was a clear shift towards higher vacancy and availability rates during the pandemic.

Figure B.2 shows that the magnitude of the increase in office vacancy is stronger in markets with a greater shift to remote work. The left panel of Figures B.2 shows that markets with a greater rise in remote work experienced a greater decline in occupancy as of the end of 2023; raising Work From Home$_{c(i)}$ by 0.15 reduces the occupancy rate by about

.05 on average. The right panel shows the timing with with these effects occurred. This chart demonstrates that the decline in occupancy in high Work From Home markets has shown little sign of abating in recent quarters.

Table B.1: Effects of Office Lease Expirations during the Pandemic, Quantile Regressions

| | $Q_{25}(\Delta\text{Occupancy})$ | | | $Q_{25}(\text{NOI Growth})$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\text{Expirations}_{i,t,t+1}$ | -0.26** | -0.27** | -0.24** | -0.22** | -0.23** | -0.21** |
| | (0.01) | (0.01) | (0.05) | (0.01) | (0.01) | (0.07) |
| $\times$ Central Business $\text{District}_{z(i)}$ | | 0.03 | 0.03 | | 0.02 | 0.02 |
| | | (0.06) | (0.05) | | (0.04) | (0.04) |
| $\times$ Work From $\text{Home}_{c(i)}$ | | | -0.11 | | | -0.06 |
| | | | (0.18) | | | (0.25) |
| COVID $\text{Expirations}_{i,t,t+1}$ | -0.17** | -0.12* | 0.38** | -0.20** | -0.17** | 0.54 |
| | (0.04) | (0.05) | (0.06) | (0.05) | (0.06) | (0.46) |
| $\times$ Central Business $\text{District}_{z(i)}$ | | -0.11 | 0.05 | | $-0.40^{+}$ | -0.16 |
| | | (0.08) | (0.09) | | (0.23) | (0.19) |
| $\times$ Work From $\text{Home}_{c(i)}$ | | | -1.96** | | | -2.67 |
| | | | (0.28) | | | (1.76) |
| $\text{COVID}_t$ | | | | | | |
| $\times$ Property $\text{Vacancy}_{i,t_-}$ | -0.11** | -0.09** | -0.09** | -0.45** | -0.41** | -0.43** |
| | (0.02) | (0.03) | (0.02) | (0.06) | (0.07) | (0.05) |
| $\times$ Central Business $\text{District}_{z(i)}$ | | -0.01* | -0.01* | | -0.01 | -0.01 |
| | | (0.01) | (0.01) | | (0.01) | (0.02) |
| $\times$ Work From $\text{Home}_{c(i)}$ | | | -0.00 | | | -0.20** |
| | | | (0.01) | | | (0.06) |
| Property $\text{Vacancy}_{i,t_-}$ | 0.02** | 0.01** | 0.01** | -0.39** | -0.39** | -0.39** |
| | (0.00) | (0.00) | (0.00) | (0.03) | (0.03) | (0.03) |
| Central Business $\text{District}_{z(i)}$ | | -0.02** | -0.02** | | 0.01 | 0.00 |
| | | (0.00) | (0.00) | | (0.01) | (0.01) |
| Work From $\text{Home}_{c(i)}$ | | | -0.00 | | | $0.07^{+}$ |
| | | | (0.00) | | | (0.04) |
| Observations | 35,482 | 35,482 | 35,482 | 35,482 | 35,482 | 35,482 |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

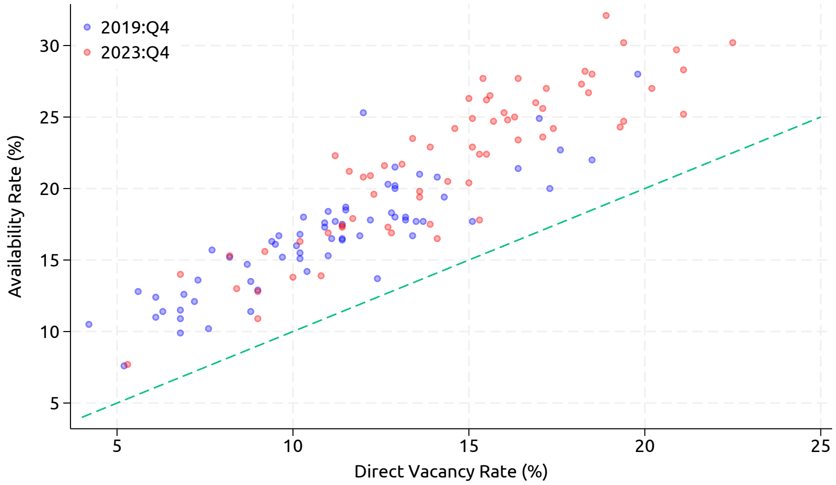
*Notes:* This table presents quantile regression estimates of the relationship between lease expirations and the 25th percentile of occupancy changes (columns 1 through 4) and NOI growth (columns 5 through 8) for office properties. $\text{Expirations}_{i,t,t+1}$ is the share of leases (in terms of square footage) set to expire over the following year, and COVID $\text{Expirations}_{t,t+1}$ interacts this expiration share with an indicator for whether $t$ is 2020 or later. Each specification follows that of the same column in Table 4, but with a quantile regression rather than OLS. $^{+}$,$^{*}$,$^{**}$ indicate significance at 10%, 5%, and 1%, respectively.
*Sources:* Morningstar, Real Capital Analytics, Opportunity Insights, and authors' calculations.

Table B.2: Effects of Pandemic Office Lease Expirations, Alternative WFH Measures

| | ΔOccupancy | | | | NOI Growth | | | |
|---|---|---|---|---|---|---|---|---|
| Work From Home Measure | Google | ACS | DN20 | HLBDST23 | Google | ACS | DN20 | HLBDST23 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Expirations$_{i,t,t+1}$ | 0.02 | -0.01 | -0.02 | 0.02 | 0.09 | 0.02 | 0.12 | 0.06 |
| | (0.08) | (0.09) | (0.10) | (0.09) | (0.14) | (0.14) | (0.15) | (0.14) |
| × Work From Home$_{c(i)}$ | -0.05 | 0.01 | 0.12 | 0.11 | -0.44* | -0.47* | -0.32 | -0.04 |
| | (0.13) | (0.13) | (0.16) | (0.16) | (0.20) | (0.20) | (0.23) | (0.25) |
| × Central Business District$_{z(i)}$ | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 | 0.00 | -0.01 | -0.01 |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.04) | (0.04) | (0.04) | (0.04) |
| × Unrenovated$_{i,t_-}$ | 0.04* | 0.04* | 0.04* | 0.04* | -0.01 | -0.01 | -0.00 | -0.01 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) |
| × ln(Price Per Sq Ft)$_{i,t_-}$ | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 | -0.01 | -0.02 | -0.04 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) |
| COVID Expirations$_{i,t,t+1}$ | -0.24 | -0.27$^+$ | -0.21 | -0.31* | -0.61* | -0.67* | -0.35 | -0.79** |
| | (0.15) | (0.15) | (0.18) | (0.15) | (0.26) | (0.27) | (0.30) | (0.27) |
| × Work From Home$_{c(i)}$ | -0.48* | -0.28 | -0.22 | -0.30 | -1.16** | -0.33 | -1.21* | -1.49* |
| | (0.23) | (0.25) | (0.32) | (0.37) | (0.41) | (0.45) | (0.61) | (0.71) |
| × Central Business District$_{z(i)}$ | -0.09 | -0.11* | -0.12* | -0.11* | -0.16 | -0.23* | -0.26* | -0.17$^+$ |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.11) | (0.10) | (0.11) | (0.10) |
| × Unrenovated$_{i,t_-}$ | -0.10** | -0.11** | -0.10** | -0.11** | -0.04 | -0.07 | -0.05 | -0.04 |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.06) | (0.06) | (0.06) | (0.06) |
| × ln(Price Per Sq Ft)$_{i,t_-}$ | 0.06* | 0.06* | 0.05$^+$ | 0.06* | 0.15** | 0.12* | 0.13* | 0.15** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.05) | (0.05) | (0.05) | (0.05) |
| COVID$_t$ | | | | | | | | |
| × Property Vacancy$_{i,t_-}$ | -0.30** | -0.30** | -0.29** | -0.30** | -0.15* | -0.17* | -0.16* | -0.16* |
| | (0.02) | (0.03) | (0.03) | (0.02) | (0.07) | (0.07) | (0.08) | (0.07) |
| × Work From Home$_{c(i)}$ | -0.13** | -0.10* | -0.11* | -0.16* | -0.30** | -0.24* | -0.28* | -0.33* |
| | (0.04) | (0.04) | (0.06) | (0.06) | (0.09) | (0.10) | (0.12) | (0.14) |
| × Central Business District$_{z(i)}$ | -0.00 | -0.01 | -0.01 | 0.00 | -0.00 | -0.01 | -0.02 | 0.00 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.02) | (0.02) |
| × Unrenovated$_{i,t_-}$ | 0.02** | 0.02** | 0.02* | 0.02* | 0.01 | 0.01 | 0.01 | 0.01 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| × ln(Price Per Sq Ft)$_{i,t_-}$ | -0.02** | -0.02** | -0.02** | -0.02** | -0.01 | -0.01 | -0.02 | -0.01 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) |
| $R_a^2$ | 0.217 | 0.217 | 0.215 | 0.217 | 0.021 | 0.021 | 0.022 | 0.021 |
| $R_a^2$(within) | 0.214 | 0.215 | 0.212 | 0.215 | 0.017 | 0.016 | 0.016 | 0.016 |
| Observations | 32,822 | 32,247 | 31,020 | 32,191 | 32,822 | 32,247 | 31,020 | 32,191 |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

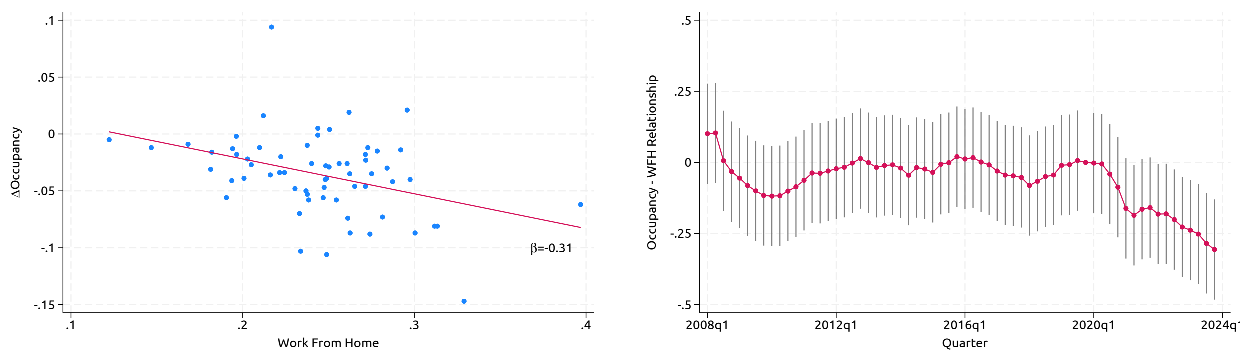
*Notes:* This table presents estimates along the lines of Columns (2) and (5) of Table 5, but using alternative measures of remote work intensity. Columns (1) and (5) repeat estimates based on Google Mobility Reports, columns (2) and (6) use ACS measures of remote work shares, columns (3) and (7) use the share of jobs in a city that can be done remotely as measured by Dingel and Neiman (2020), and columns (4) and (8) use the share of job postings in a city that allow for remote work from Hansen et al. (2023). Standard errors, in parentheses, are clustered by loan. $^{+,*,**}$ indicate significance at 10%, 5%, and 1%, respectively.
*Sources*: Morningstar, CBRE, Opportunity Insights, data shared by above papers, and authors' calculations.

Figure B.1: Office Vacancy and Availability




*Notes:* This figure presents a scatter plot of availability rates by vacancy rate for CBRE office markets as of 2019:Q4 (blue) and 2023:Q4 (red).
*Sources:* CBRE.

Figure B.2: Relationship between Work from Home and Office Occupancy Rate




(a) Change in Office Occupancy during COVID

(b) Occupancy over Time

*Notes:* The left figure presents a scatter plot between the change in office occupancy (from 2019:Q4 to 2023:Q4) and the decline in time spent at workplaces during the pandemic for markets covered in the CBRE database. Work From Home$_m$ is the population weighted average across the counties in market $m$. The right chart presents estimates of $\{\beta_t\}$ and 95% confidence intervals from the specification:

$$\text{Occupancy}_{m,\tau} = \alpha_m + \alpha_t + \sum_{t \in T} \beta_t \text{Work From Home}_m \times \mathbb{1}(\tau = t),$$

representing how occupancy changes in markets with a high 2022 work-from-home share over time.
*Sources:* CBRE, Opportunity Insights, and authors' calculations.

# C Bank Exposures to At-risk Office Markets: Additional Results

This section presents evidence that banks, especially smaller banks, are less exposed to CBD office loans than other CRE lenders because they generally make smaller loans, which tend to be located more in suburban markets. Table C.1 analyzes the exposure of non-G-SIB/foreign banks (columns 1 through 3) and community banks (columns 4 through 6) to at-risk office loans. It shows that office loans in CBDs, or counties with a higher remote-work intensity, are less likely to be held by small and regional domestic banks (column 1) or community banks [18]. The coefficient estimates change little with the inclusion of core-based statistical area (CBSA) fixed effects, meaning that the differences are driven by locations *within* cities rather than across cities (columns 2 and 5). Namely, smaller banks do more lending in suburban markets, where demand appears to have fallen less than it has around city centers. Finally, the estimated differences in exposure to high-risk markets fall to almost zero when we control for loan size, indicating that the results are due to smaller banks making smaller loans (columns 3 and 6).

[18] Non-G-SIB/foreign bank loans are identified as loans RCA identifies as bank loans but do not have a name associated with a G-SIB or major foreign bank (which are name matched by hand). Community banks are banks that are successfully fuzzy-name-matched to Call report data, and are linked to banks with under \$10 billion in assets.

Table C.1: Determinants of Bank Exposure to At-risk Office Loans

| | Non-GSIB/Foreign Bank Indicator | | | Community Bank Indicator | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Work From Home$_{c(i)}$ | -0.92** | -0.78** | -0.34** | -0.42** | -0.31** | -0.12 |
| | (0.11) | (0.11) | (0.09) | (0.11) | (0.08) | (0.08) |
| Central Business District$_i$ | -0.09** | -0.10** | -0.04** | -0.02* | -0.03** | -0.01 |
| | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| ln(Price Per Sq Ft)$_{i,t}$ | -0.01 | -0.01 | 0.02** | -0.02** | -0.02** | -0.00 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.00) | (0.00) |
| Unrenovated$_{i,t}$ | 0.10** | 0.11** | 0.06** | 0.05** | 0.05** | 0.03** |
| | (0.01) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) |
| ln(Loan Amount) | | | -0.10** | | | -0.04** |
| | | | (0.01) | | | (0.00) |
| $R^2_a$ | 0.033 | 0.058 | 0.105 | 0.015 | 0.057 | 0.073 |
| Observations | 37795 | 37660 | 37660 | 37795 | 37660 | 37660 |
| CBSA FEs | | ✓ | ✓ | | ✓ | ✓ |

*Notes:* This table presents estimates of a linear probability model predicting whether a lender is a non-G-SIB-bank (columns 1 through 3) or a community bank (columns 4 through 6) based on whether the property securing a loan is in a central business district and the decline in the time spent at workplaces. The second and third columns in each set add in CBSA fixed effects and a control for the size of the loan, respectively. The sample is of office loans reported in RCA that we imputed to be outstanding outstanding as of 2023q1, as described in Section 5.2. Community banks are those with under \$10 billion in assets. $^{+}$,$^{*}$,$^{**}$ indicate significance at 10%, 5%, and 1%, respectively.
*Sources*: Real Capital Analytics, Opportunity Insights, and authors' calculations.