Commercial Mortgage Debt Overhang and Intent to Default

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Abstract

This paper investigates whether investment in leasing activity by property owners is associated with default risk for CMBS loans on office buildings. We conjecture that borrowers, who possess superior knowledge of their properties, make investment decisions that reflect their private valuations. When a borrower perceives a property's value to be lower than the outstanding loan balance, further investment primarily benefits the lender, creating a classic debt overhang problem Myers (1977). This suggests that leasing effort and tenant improvement expenditures, relative to a property's competitive set, may serve as indicators of intention to default. Consistent with this hypothesis, we find that lower leasing effort by borrowers is associated with a higher likelihood of loan delinquency.

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1 Introduction

The U.S. office sector is undergoing a major repricing. As of late 2024, national vacancy rates reached a record high of 20.9% driven by the rise of remote and hybrid work and a persistent oversupply of functionally obsolete buildings (Cushman & Wakefield, 2025; Brookfield, 2024). As demand for office space declines in local user markets, landlords tend to offer increasingly generous lease concessions—primarily, free rent periods and tenant improvement allowances (TIs)—to attract and retain tenants. These concessions help accelerate lease-up and incentivize longer lease terms, thereby reducing vacancy duration costs, particularly when demand is weak.[1]

In frictionless markets, landlords would make such investments whenever the expected net present value (NPV) is positive. However, the commercial real estate sector is highly levered, and investment incentives may be distorted by capital structure. Once loan-to-value ratios exceed unity due to changing market conditions, incremental improvements in occupancy are likely to accrue primarily to lenders, creating a classic debt overhang problem (Myers, 1977).

While our objective is to examine whether leasing investment is constrained by borrower leverage, an empirical challenge is that the theoretical construct of borrower leverage is contemporaneous leverage, which depends on accurate estimates of current asset value. In practice, such estimates can be difficult to obtain, especially during market downturns when property transactions slow, reducing the reliability of standard valuation metrics. Moreover, many of the key determinants of a property's competitiveness—such as location quality, internal configuration, and surrounding neighborhood amenities—are difficult to observe or quantify from the perspective of a credit risk holder or econometrician.

Because the owner is likely to have superior information about the attributes of their properties, leasing investments may reveal private information, offering a view into the borrower's internal assessment of the asset's long-term viability. As such, we conjecture that leasing expenditures may function not only as a margin of adjustment but also as a proxy for unobservable asset quality and strategic borrower intent.

In this paper, we use data on leasing expenditures by landlords of office properties collateralizing securitized mortgages to test these interrelated hypotheses in a two-stage strategy. In the first stage, we separately estimate two measures of a property owner's leasing investment:

[1]For example, although the commercial real estate services firm CBRE recently reported some pullback in concession packages, average concession values remain approximately 30% above their pre-pandemic levels (CBRE, 2025). This persistence suggests that, even amid evolving market conditions, landlords continue to view concessions as a viable strategy for enhancing asset performance.

months of free rents and tenant improvement allowances. In the second stage, we incorporate the residuals from these estimates—representing deviations from expected leasing investment—into models that explain alternative measures of loan delinquency and default, consistent with leasing expenditure conveying private information about borrower valuations and default decisions.

Our study primarily relates to the literature on commercial mortgage default. This literature has moved beyond early contingent claims models, which treat default as a put option, exercised when the market value of the property falls below the loan balance (Black and Scholes, 1973; Merton, 1974; Vandell, 1992). However, a large body of empirical work rejects the prediction of "ruthless" default behavior, emphasizing instead that commercial mortgage borrowers often delay default, seek modification, or continue to invest in troubled properties.

Recent theoretical frameworks attribute this behavior to strategic interactions between borrowers and lenders under conditions of market illiquidity and renegotiation frictions (Riddiough and Wyatt, 1994; Brown et al., 2006). Borrowers weigh the costs of default against expectations about lender behavior, the property's long-run income potential, and the availability of loan modifications. In this context, observable borrower actions, such as leasing investment, may contain information not only about current property conditions but also about expectations and incentives.

We contribute to this literature by providing new evidence of debt overhang in a commercial real estate setting. We show that variation in leasing investment, conditional on property and market fundamentals, predicts subsequent loan performance, consistent with a private-information channel and an association between leasing expenditures and leverage. Our identification strategy exploits variation in rent abatement and tenant improvement allowances across properties and time to estimate the conditional relationship between leasing effort and delinquency outcomes.

Prior empirical studies have explored related ideas in residential housing (Melzer, 2017), hotel operations (DeFusco et al., 2023), and retail leasing (Liebersohn and Correa, 2022). Our focus on the office sector during a period of structural change allows us to isolate borrower behavior in a market where default risk is rising, asset values are volatile, and investment decisions are particularly salient. To our knowledge, this is the first study to use landlord leasing effort as a leading indicator of commercial mortgage performance.

The next section of the paper describes our sample, which we compile from two sources: lease transactions from CompStak and CMBS loan data from Trepp. While both datasets are commonly used in research on commercial real estate, our approach of merging them appears to be novel in the literature. Our two-stage empirical strategy is detailed in Section 3. Results presented in Section 4, indicate that, as expected, higher levels of leasing investment are associated with lower levels of delinquency in the next quarter. Section 5 concludes the paper with a discussion of the next steps for the project.

2 Data

We obtain detailed lease transactions for office properties from CompStak, who claim to have the most reliable and complete data on commercial leases in the United States.[2] The CompStak dataset contains extensive details on individual leases, including rent, lease term, leased area, lease type (net or gross), execution and expiration dates, and transaction type (new lease or renewal). Additionally, it provides individual tenant characteristics, including firm name, industry classification, and ownership structure (public vs. private). Furthermore, the dataset includes comprehensive property-level attributes, such as physical address, geographical coordinates, total rentable area, building age, and building quality categorization (Class A, B, or C).

Important for our purposes, the CompStak data include variables that capture a property owner's investment in leasing, including allowances for tenant improvements and free rent concessions. By leveraging this rich dataset, we can quantify leasing investments and strategic decisions at the individual lease level, which is particularly valuable for analyzing the relation between borrower leasing behavior and the likelihood of mortgage default.

We obtain data on CMBS loans from Trepp, which aggregates information from multiple sources to providing comprehensive coverage of loan characteristics and performance. At the property level, the Trepp dataset includes detailed financial and physical attributes such as the debt service coverage ratio (DSCR), loan-to-value (LTV) ratio, geographic location, and property classifications. Notably, it also tracks the proportion of leases set to expire within the next twelve months, which we use to evaluate a property owner's performance in managing lease expirations through timely renewals or tenant replacements. At the loan level, Trepp provides extensive details on initial loan terms, including origination characteristics, pricing information,

[2]CompStak collects transaction-level leasing data directly from real estate brokers and market participants, who voluntarily contribute data on completed lease agreements. Contributors are incentivized to share proprietary lease information in exchange for access to similar market data from their peers. Each submitted lease record undergoes validation processes by CompStak to ensure accuracy, internal consistency, and credibility of the reported terms.

and monthly updates on loan payment status and delinquency indicators.

To merge the CompStak and Trepp datasets, we use PlaceKey,[3] a widely-adopted universal location identifier designed to standardize geospatial data across multiple sources. The PlaceKey identifier comprises two distinct parts: the "What" component, representing specific entities or tenants at a location, and the "Where" component, indicating the precise geospatial coordinates of a property. For instance, LinkedIn's office at the Empire State Building has a PlaceKey formatted as "13e6bubf5c@627-s8k-2rk," where the "13e6bubf5c" (the "What") uniquely identifies LinkedIn at that location, while "627-s8k-2rk" ("Where") specifies the Empire State Building's location. In our analysis, we utilize both the "What" and "Where" components: the "What" component identifies individual tenants (from CompStak), while the "Where" component precisely matches these tenants to their corresponding buildings (from Trepp). This dual-component matching facilitates an accurate and detailed integration of leasing data and loan performance data, enabling us to rigorously investigate borrower leasing behavior in relation to default outcomes.

Our sample period is from 2000Q1 to 2024Q4. Our initial sample construction identified 89,131 unique office properties (or 623,894 leases) in the CompStak dataset, of which 88,135 (or 595,166 leases) were successfully geocoded. From Trepp, we identified 239,983 loan-property observations and successfully matched 24,368 with CompStak data. After merging the geocoded properties, we obtained a dataset of 110,000 loan-property observations across 35,000 unique properties. After excluding subleases and observations with missing tenant improvement data, we obtain a final sample of 5,040 loan-property observations. This dataset provides 82,399 monthly loan-level observations for analysis.

Table A.2 addresses potential concerns about selection bias in our merged CompStak-Trepp dataset. Specifically, we estimate regressions using the entire CompStak sample and define the dependent variable as an indicator equal to 1 if an observation is included in our merged CompStak-Trepp sample, and 0 otherwise. Column (1) examines whether properties offering tenant improvement allowances (indicated by $ti\_yes = 1$ if tenant improvement > 0, 0 otherwise) are systematically different in the matched sample. The coefficient on the leasing variable (ti_yes) is negative and marginally significant, suggesting minimal differences in leasing activity between matched and unmatched samples. In Column (2), we use free rent concessions ($fr\_yes = 1$ if free rent > 0, 0 otherwise) as our key variable. This

[3] https://www.placekey.io

variable is insignificant, further alleviating selection concerns regarding leasing incentives. While other property characteristics such as transaction size, building size, renewal status, property age, and distance from CBD exhibit significant differences across matched and unmatched samples, the insignificant or marginally significant results for our key leasing variables suggest that our primary analyses related to landlord leasing decisions are unlikely to be substantially impacted by selection bias from the sample-matching process.

3 Methodology

Our empirical analysis consists of two stages. In the first stage, we estimate two measures of a property owner's leasing activity, Tenant Improvement Allowances and Months of Free Rent, both at the lease level.

For lease l, borrower i on property j in location m during year-quarter t, our lease-level first-stage regression is as follows:

$$\begin{aligned}\text{Leasing Investment}_{l,i,j(m),t} = &\ \boldsymbol{\beta}\,\text{Lease Characteristics}_{i,t-1} + \boldsymbol{\gamma}\,\text{Property Characteristics}_{j,t-1} \\ &+ \boldsymbol{\delta}\,\text{Location}_m + \psi_m + \phi_t + \epsilon_{l,i,j,m,t},\end{aligned} \tag{1}$$

where *Leasing Investment* refers alternately to the dollar amount of tenant improvement allowances per square foot of leased area or the number of months of free rent concessions granted at lease signing.

The explanatory variables in the first-stage equations are lease, property, and location characteristics. The vector of *Lease Characteristics* includes lease size in natural log of square feet, and an indicator for whether the lease was a renewal. *Property Characteristics* include building class indicators, building size in natural log of square feet, property age, and years since renovation. We use distance to the central business district (CBD), following Holian (2019), as a proxy for *Location* quality. Fixed effects, ψ_m and ϕ_t, are MSA and year-by-quarter, respectively. All regressions use robust standard errors clustered at the MSA level.

We retain the residuals from estimating Equation 1 as measures of leasing effort, relative to the average level observed in comparable properties within the immediate submarket. The residuals from estimating Equation 1 are aggregated to the property-level. These residuals then serve as proxy variables for the borrower's "Intent to Default" in Equation 2 that follows.

Following Agarwal et al. (2024), the dependent variable in our second-stage equation consists of alternative measures of loan delinquency and default: 30, 60, and +90 days delinquent, and non-performing maturity default. For loan n, borrower i on property j in location m during year-quarter t, our second-stage regression is as follows:

$$\begin{aligned} \text{Loan Default}_{n,(i,j,m),t} = {} & \beta\, \widehat{\text{Intent to Default}}_{n,t-1} + \boldsymbol{\lambda}\, \text{Loan Characteristics}_{n,t-1} \\ & + \boldsymbol{\gamma}\, \text{Property Characteristics}_{j,t-1} + \boldsymbol{\delta}\, \text{Location}_m \\ & + \boldsymbol{\theta}\, \text{Current Interest Rate}_{t-1} + \kappa_j + \rho_n + \tau_{n,t} + \zeta_n + \epsilon_{n,t}. \end{aligned} \tag{2}$$

Intent to Default in Equation 2 is the residuals from Equation 1, aggregated from lease transaction level to property-year-quarter level.

A positive coefficient of β would suggest that our proxy for the borrower's *Intent to Default*, could predict the actual loan default in the subsequent year. The Loan Characteristics variable includes the loan balance, Loan-to-Value Ratio, Debt Service Coverage Ratio, and the interest rate at origination. The Current Interest Rate is the Annualized yield on 10-year treasury securities. κ_j, ρ_n, $\tau_{n,t}, \zeta_n$ are Property Type, Originator, Origination Year/Month, and Origination State fixed effects respectively.

Additionally, the loan characteristics vector will include contemporaneous LTV and DSCR, the interest rate at origination, and potentially the change in net operating income (NOI) since origination to better capture financial conditions affecting default risk.

OLS estimates of Equation 2 may be biased because OLS does not account for right censoring in the data, which arises naturally in our data due to loans that remain performing at the end of the study period. Given that most loans have not defaulted within the observation window, ignoring censoring can lead to biased estimates.

To address these issues, we plan to estimate the default equation using hazard models, which are widely used in mortgage research due to their ability to account for right censoring and model the timing of default events more effectively.

4 Preliminary Findings

4.1 Intent to Default

Table 1 provides summary statistics for our lease-level sample with variable definitions provided in Appendix A.1. At the lease level, the variable *TI* (tenant improvement allowances) has an average value of \$12.81 with a standard deviation of \$25.44, indicating considerable variation in tenant improvement costs across the sample of 192,221 observations. The *FR* (free rent) variable has a mean of 2.00 months and a standard deviation of 3.34 months. The average transaction size, *Transaction SQFT*, is 13,130 square feet. About 26.0% of transactions are renewals.

For Building Characteristics, *ClassA* buildings make up approximately 47.0% of the sample, with a standard deviation of 0.50, indicating a relatively even split between Class-A and non-Class-A buildings. *Building Size* averages 346,329 square feet with a standard deviation of 428,645 square feet, reflecting a broad range of building sizes. The average *Property Age* (*propage*) is around 47 years, with a standard deviation of 28.38 years.

On average, Years Since Renovation (*yrsincerenov*) is 12.27 years, with a similar standard deviation of 14.12 years, showing that many buildings have undergone renovation within the last decade. The average distance from the central business district (CBD), represented by *km_to_nid*, is approximately 12.42 kilometers, with a standard deviation of 14.00 kilometers, indicating a wide distribution of property locations relative to the CBD. Approximately 30% of lease transactions involve publicly owned landlords, whereas only about 7% of leases are with publicly traded tenants. Regarding lease transaction type, new leases constitute roughly 48.9% of the sample, with the remainder consisting of lease renewals. Additionally, leases are classified by rent structure, with about 22.2% structured as net leases and the remainder as gross leases.

Table 2 provides estimates of Equation 1. The regression results show the relationships between the two outcomes, including *tenant improvement costs (TI)* and *free rent (FR)*,and a set of lease-specific, property-level, and location-based characteristics.

In the first model, which examines the determinants of *TI*, we see that the *log of transaction size (lntransactionsqft)* has a highly significant positive effect, with a coefficient of 4.434, indicating that larger transactions lead to higher tenant improvement costs. Similarly, *ClassA* buildings are associated with significantly higher tenant improvement costs, as the coefficient for ClassA is 4.995. The *log of building size (lnbldgsize)* is also positively related to TI, suggesting that larger buildings incur higher tenant improvement costs. *Years since renovation (yrsincerenov)* and *distance to CBD* both have significant negative coefficients (-0.105 and -0.169, respectively), implying that buildings that have been renovated more recently and those farther from the CBD tend to have lower tenant improvement costs. Additionally, the *renew* variable shows a strong negative effect, with a coefficient of -7.997, suggesting that renewals lead to significantly lower tenant improvement costs compared to new leases. The model explains 20.4%

of the variance in tenant improvement costs, as indicated by the R-squared value.

In the second model, which focuses on *FR* (free rent), *lntransactionsqft* again has a positive and significant effect, with a coefficient of 0.611, indicating that larger transaction sizes are associated with more free rent offered to tenants. *ClassA* buildings are also associated with more free rent (0.661), and *lnbldgsize* shows a smaller but still significant positive effect. *renew* has a negative coefficient (-0.824), meaning renewals tend to result in less free rent than new leases. Similar to the first model, *yrsincerenov* and *distance2CBD* are both negatively correlated with free rent, meaning more recent renovations and properties located farther from the CBD are associated with lower free rent. This model explains 23.1% of the variance in free rent, as shown by the R-squared value.

Overall, our findings in Table 2 reveal consistent patterns across both models. First, larger lease transactions and larger buildings consistently incur higher tenant improvement allowances and more generous concessions, such as free rent. Notably, new leases tend to require significantly greater investment from landlords, reflected by higher tenant improvement (TI) allowances and more generous free rent (FR) concessions compared to lease renewals. Properties that have recently undergone renovations or those located closer to the central business district (CBD) exhibit lower landlord investment requirements, suggesting these assets are better positioned competitively and attract tenants requiring fewer inducements. Conversely, older, less recently renovated, and more peripheral properties require lower landlord investment, likely reflecting landlords' reduced incentives due to lower expected returns. Taken together, these findings underscore that landlords strategically adjust their leasing investment decisions based on property quality, lease type, and proximity to core market locations. These leasing decisions likely reflect landlords' private valuations and anticipated financial distress, potentially signaling their intent to default.

4.2 Default

Table 3 provides the summary statistics for the variables in Equation (2). These include loan performance characteristics as follows. The delinquency-related variables, including *LatePmt* (late payment), *Dlq30plus* (delinquency 30 days or more), *Dlq60plus* (delinquency 60 days or more), and *Dlq90plus* (delinquency 90 days or more), have relatively low means, with values of 0.033, 0.008, 0.007, and 0.006, respectively. The estimated residuals for *ti_resid* (tenant improvement residuals), and *fr_resid* (free rent residuals) were obtained from Equation 1. Figure

2 shows the geographic distribution of late payments in our sample, highlighting that our sample is not constrained to one geographic area.

The loan characteristics show significant variation. *Original loan balance (origloanbal)* has a mean of $79.9 million with a large standard deviation of $130 million, indicating a wide range of loan sizes, from smaller loans (p25 = $15 million) to larger ones (p75 = $95 million). The average current loan-to-value ratio, *ltv*, is 69.6%, but the high standard deviation (142.8%) suggests some extreme cases with higher current LTV values. The mortgage rate, *actrate*, has a mean of 5.69% and standard deviation of 9.79%, with the 25th, 50th, and 75th percentiles at 4.94%, 5.59%, and 6.14%, respectively.

Table 4 presents pairwise correlation coefficients among key variables in our analysis. Both tenant improvement residuals (ti_resid) and free rent residuals (fr_resid) show negative correlations with late payments. These observations are consistent with our expectation that lower leasing activity is related to greater delinquency risk. Loan-level characteristics, notably loan-to-value (ltv) and mortgage rates (actrate), display strong correlations with late payments, suggesting higher leverage is associated with increased delinquency likelihood. Conversely, larger original loan balances (origloanbal) show a negative correlation with late payments, indicating loans of greater size tend to exhibit lower delinquency rates. Additionally, property-level characteristics such as building age (propage) and years since last renovation (yrsincerenov) are negatively correlated with late payments, suggesting that older properties or those with longer intervals since renovation are more likely to experience loan delinquency. Finally, distance from the central business district (km_to_nid) is positively correlated with late payments, indicating properties farther from the CBD have higher delinquency risks.

Table 5 provides estimation results of Equation 2. The regression results show the relationship between intent to default and default, proxied by *LatePmt* (late payment). Each model has 82,399 observations and controls for fixed effects related to property type, originator, loan origination year-month, and state. The dependent variable is *LatePmt*, indicating loan delinquency status. Column (1) examines the relationship between late payments and tenant improvement residuals (*ti_resid*), which exhibit a negative and significant coefficient (-0.019). This suggests that lower spending on tenant improvements relative to peers significantly predicts higher default risk. Column (2) investigates the effect of free rent residuals (*fr_resid*) on late payment. This variable also shows a negative, marginally significant relationship (-0.101), indicating that lower provision of concessions in the form of free rent is weakly associated with increased late payments.

The control variables have expected signs. Larger original loan balances (*lnorigloanbal*) are consistently associated with lower probabilities of late payments, while higher debt service coverage ratios (*dscrnoi*) are positively correlated with late payments. Older properties (*propage*) and properties that have gone longer without renovation (*yrsincerenov*) also exhibit significantly higher default risks.

Overall, these second-stage regression results strongly support our hypothesis that lower leasing effort and reduced landlord investment, particularly tenant improvement expenditures, signal a borrower's elevated intent to default, as evidenced by higher delinquency probabilities.

Table 6 presents results from the second-stage regressions using delinquency indicators as outcome variables and tabulates the results for alternative forms of delinquency, including *Dlq30plus* (delinquency 30 days or more), *Dlq60plus* (delinquency 60 days or more), and *Dlq90plus* (delinquency 90 days or more). Columns 1 and 2 focus on loans delinquent by 30 days or more (*Dlq30plus*). The results show that the tenant improvement residual (*ti_ resid*) has a significantly negative relationship (-0.015), suggesting that lower tenant improvements are linked to increased delinquency. Additionally, lower free rent residuals (*fr_ resid*) also weakly predict higher delinquency rates (coefficient = -0.082).

Columns 3-6, which consider delinquencies of 60 days or more (*Dlq60plus*) and 90 days or more (*Dlq90plus*), yield results consistent with those in Columns 1 and 2. Reduced tenant improvement allowances consistently signal greater delinquency probabilities (-0.014). The patterns reinforce the conclusion from Panel A: lower landlord investment activity is associated with higher loan delinquency risks, supporting our core hypothesis regarding landlords' intentions to default.

Table 7 presents cross-sectional heterogeneity tests to examine how the relationship between leasing investment and late payment varies by landlord and tenant characteristics as well as lease types. The dependent variable in all regressions is an indicator for late payment. The control variables are the same as our baseline results in Table 5.

Columns 1–5 explore heterogeneity in tenant improvement residuals (*ti_ resid*). Column 1 differentiates between public and private landlords. We classify a landlord as public if the property involved in the lease transaction matches any property owned by a publicly listed company in S&P Global. We construct two separate residuals in the first-stage analysis: *hetero_ yes* represents residuals from the first stage regression using lease transactions involving public landlords, while *hetero_no* represents residuals from private landlord transactions. In the second stage, these residuals are aggregated and included separately. The residual for public landlords (*hetero_yes*) is negative but insignificant, whereas the residual for private landlords (*hetero_no*) is negative and significant (-0.028), indicating a stronger relationship between reduced tenant improvements and delinquency risk among private landlords.

Column 2 suggests the relationship between (*ti_resid*) and late payment is stronger among private tenants. Landlords might strategically reduce investments in private tenants because they anticipate greater default or payment uncertainty from private tenants who typically have weaker financial conditions compared to publicly traded tenants. Thus, tenant ownership type may proxy for tenant credit risk or uncertainty, indirectly influencing landlords' investment decisions and signaling landlord intent to default.

In Column 3, we classify tenants into "small" versus "large" based on their total occupied square footage in year t-1. The results suggest that the predictability for late payment is significant only among large tenants. Large tenants generally occupy significant portions of a building, meaning their financial stability and renewal likelihood have disproportionately large impacts on a landlord's revenue stream. When landlords perceive that a large tenant is at risk of vacating or defaulting, they may reduce investment in tenant improvements strategically to minimize losses, thereby sending a stronger signal about their intentions regarding potential default.

Both coefficients of (*hetero_yes*) and (*hetero_no*) are negative and statistically significant in Columns 4–5. However, we observe stronger associations of reduced tenant investment with late payments for renew and gross leases. The stronger association of reduced tenant investment with late payments observed among renewal (as opposed to new) leases may reflect landlords' strategic responses tied to updated information about tenant stability. Renewal leases often involve existing tenants whose financial positions and lease performance are already known to landlords. Therefore, when landlords deliberately scale back tenant improvements during renewals, it may strongly signal their lowered expectations of tenant viability or property-level cash flow sustainability. In contrast, new leases inherently involve more uncertainty, and initial investments may be necessary to attract tenants regardless of future expectations. On the other hand, the stronger relationship found for gross leases compared to net leases could be attributed to the greater financial obligations landlords bear under gross lease structures. Because landlords cover most operating expenses under gross leases, their incentives in tenant improvements will be stronger if their cash flow expectations are positive. Thus, reduced investment in tenant improvements for gross leases may be a clearer indication of anticipated financial distress or strategic intent to default, as landlords become reluctant to absorb these costs under uncertain future cash flows.

Columns 6–10 show these tests using free rent residuals (*fr_resid*) as the primary variable of interest. Results in Columns 6-8 generally align with those for tenant improvements, though the statistical significance and magnitude vary slightly. However, in contrast to Columns 4–5 (tenant improvement results), Columns 9–10 reveal a stronger negative association for new and net leases, indicating that reductions in free rent concessions more strongly signal delinquency risk for these lease types. One plausible explanation is related to the distinct roles these incentives play in leasing strategies. Free rent concessions are immediate, short-term landlord investments intended to attract tenants quickly and mitigate near-term vacancy risks, especially crucial in new leases where the landlord faces greater initial uncertainty. Net leases, in which tenants bear more operating expenses, require fewer landlord incentives under normal circumstances. Consequently, a noticeable reduction in free rent concessions for net leases can strongly signal a landlord's immediate intent to minimize short-term cash outflows amid financial constraints. Thus, the strategic reduction in free rent concessions for new and net leases likely reflects landlords' immediate anticipation of financial distress. Financially constrained landlords may be more likely to cut flexible, short-term incentives (such as free rent) as a rapid response to anticipated default risk.

Overall, the heterogeneity analyses suggest that the signal of landlord investment in predicting default risk varies meaningfully across different landlord types, tenant characteristics, and lease structures.

Table 8 extends the cross-sectional heterogeneity analysis from Table 7 by examining how leasing investment relates to various delinquency durations. Specifically, Panel A uses an indicator for delinquency of 30 days or more (Dlq30plus), Panel B uses delinquency of 60 days or more (Dlq60plus), and Panel C examines delinquency of 90 days or more (Dlq90plus). Control variables are the same as the previous table and suppressed for brevity.

Results in all three panels are highly consistent. In Column 1, tenant improvement residuals (*ti_resid*) show that private landlords (*hetero_no*) have significantly stronger negative associations with delinquency, while public landlords' associations are not significant. In Column 2, both private and public tenants demonstrate significant negative associations, indicating reduced tenant improvements predict delinquency for both tenant types. Large tenants (Column 3) also exhibit a stronger negative relationship, further highlighting the predictive power of tenant improvements for this group. Columns 4 and 5 indicate significant negative relationships for renew and gross leases. Results in Columns 6-10 focusing free rent residuals (*fr_ resid*) are generally weaker in terms of statistical significance. However, we observe consistent patterns that the predictability is strong among private landlords, private tenants, large tenants, renewal leases, and net leases.

Comparing these results to Table 7, which uses late payment as the outcome, we observe notable differences. Specifically, in Column 3, while Table 7 (using late payment as the outcome) finds that lower tenant improvement expenditures significantly predict delinquency predominantly among private tenants, Table 8 (using longer-term delinquency indicators) demonstrates significant predictive effects from both private and public tenants. In Columns 4-5, while Table 7 show significant results for both groups, 8 show significance only among renewal and gross leases. Moving to the results focusing on free rent residuals (in Columns 6-10), while neither public landlords nor private landlords significantly explains late payment in Table 7, the results for private landlords become statistically significant in Table 8. These results suggest that the signal from landlord investment in tenant improvements becomes more broadly relevant across tenant ownership types as delinquency duration lengthens.

5 Conclusion

The supply-demand imbalance in the office sector, described in Section 1, has been exacerbated by high interest rates, driven by the Federal Reserve's efforts to curb inflation. Higher rates since 2022 have increased debt service obligations and lowered property valuations, leading to a rise in both term and maturity defaults on mortgage loans. For example, delinquency rates on office loans within commercial mortgage-backed securities (CMBS), surged from 6% to 11% over the past year, reflecting these increasing economic and financial pressures (Commercial Real Estate Direct and Trepp, 2025).

This paper examines strategic default behavior in commercial mortgage markets, focusing on the borrower's private information and its potential observability through leasing expenditure. We argue that leasing investment reveals a borrower's intent to retain the asset and avoid default. Using proprietary lease-level data from CompStak, we construct a novel measure of lagged leasing activity and incorporate it into a default prediction framework for office-backed CMBS loans. Our empirical models, estimated on loan-level data from Trepp, control for local market fundamentals, property quality, and loan terms.

Our findings suggest that reduced leasing activity in the quarter preceding delinquency is significantly associated with loan default, consistent with the hypothesis that leasing investment conveys inside information about the borrower's default intent. These results contribute to a growing literature on the role of borrower behavior and asymmetric information in mortgage outcomes and may inform lender decisions regarding loan structuring and modification strategies.

While this version of the paper fulfills the objectives outlined in our proposal to the Real Estate Research Institute, we intend to extend the analysis along several dimensions in future revisions.

First, conditional on access to additional property-level financials, we aim to estimate contemporaneous loan-to-value ratios and directly test how leverage affects leasing investment. This would allow for a more structural interpretation of the link between financing frictions and investment decisions.

Second, we plan to explore heterogeneity in borrower behavior. We hypothesize that the propensity to continue leasing efforts and avoid default during downturns is influenced not only by asset and market characteristics, but also by borrower-specific factors, including liquidity reserves, capital structure, investment horizon, portfolio diversification, operational capabilities, and lender relationships. This analysis will depend on access to richer borrower-level data.

Finally, we intend to refine our empirical framework. Specifically, we plan to examine alternative lag structures between leasing activity and observed outcomes, and to adopt a competing risks model that more appropriately captures the multi-outcome nature of commercial mortgage performance. Such models accommodate the possibility of prepayment, maturity payoff, loan modification, or continued performance, in addition to default. This approach would also permit sharper tests of the theoretical predictions introduced in Section 1, particularly regarding the signaling role of leasing investment and asymmetric information.

References

Agarwal, S., Ambrose, B. W., Yildirim, Y., and Zhang, J. (2024). Risk retention rules and the issuance of commercial mortgage backed securities. *The Journal of Real Estate Finance and Economics*, 68(4):684–714.

Black, F. and Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of political economy*, 81(3):637–654.

Brookfield (2024). The misunderstood u.s. office market. Retrieved from `www.brookfield.com/news-insights/insights/misunderstood-us-office-market`.

Brown, D. T., Ciochetti, B. A., and Riddiough, T. J. (2006). Theory and evidence on the resolution of financial distress. *The Review of Financial Studies*, 19(4):1357–1397.

CBRE (2025). Top-tier office rents continue to rise, while lower-tier rents fall. Retrieved from `https://www.cbre.com/insights/briefs/top-tier-office-rents-continue-to-rise-while-lower-tier-rents-fall`.

Cushman & Wakefield (2025). U.s. office marketbeat report. Retrieved from `https://www.cushmanwakefield.com/en/united-states/insights/us-marketbeats/us-office-marketbeat-reports`.

DeFusco, A. A., Nathanson, C. G., and Reher, M. (2023). Real Effects of Rollover Risk: Evidence from Hotels in Crisis. *National Bureau of Economic Research Working Paper Series*, No. 31764.

Direct, C. R. E. and Trepp (2025). 2024 year-end 2024. Retrieved from `www.trepp.com/trepp-cre-direct-year-end-magazine-2024`.

Holian, M. J. (2019). Where is the City's Center? Five Measures of Central Location. *Cityscape*, 21(2):213–226.

Liebersohn, J. and Correa, R. (2022). Debt Overhang and the Retail Apocalypse.

Melzer, B. T. (2017). Mortgage Debt Overhang: Reduced Investment by Homeowners at Risk of Default. *The Journal of Finance*, 72(2):575–612.

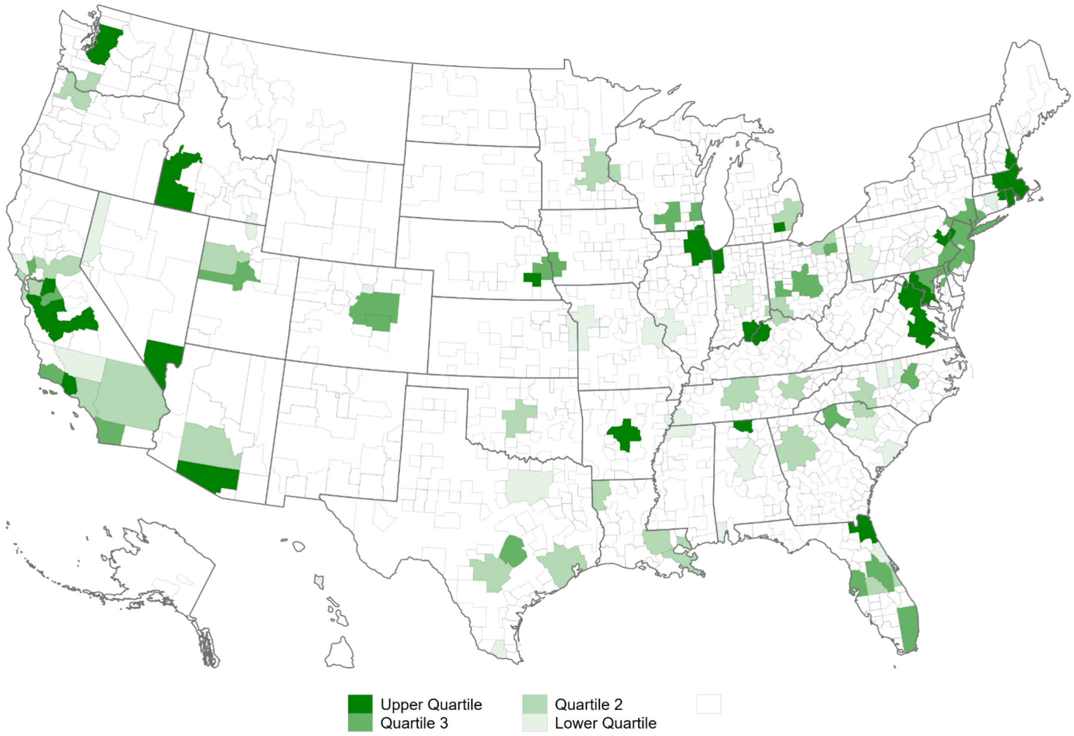
Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance*, 29(2):449–470.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5(2):147–175.

Riddiough, T. J. and Wyatt, S. B. (1994). Strategic default, workout, and commercial mortgage valuation. *The Journal of Real Estate Finance and Economics*, 9:5–22.

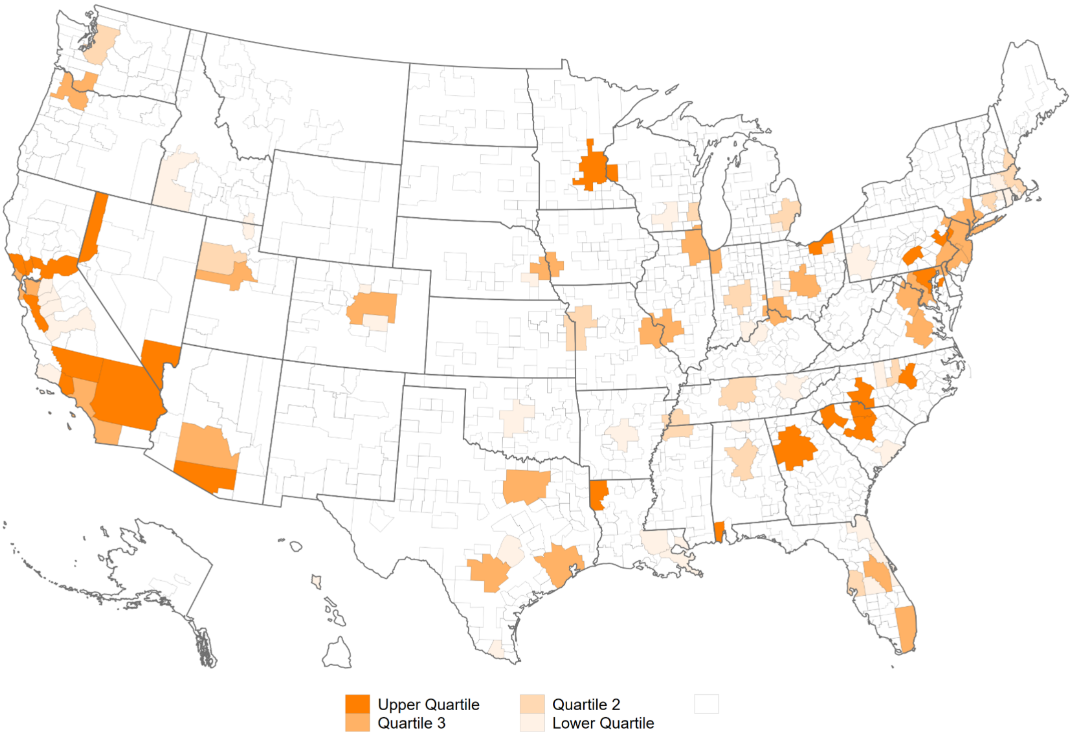
Vandell, K. D. (1992). Predicting commercial mortgage foreclosure experience. *Real Estate Economics*, 20(1):55–88.

Figure 1: TI Residuals



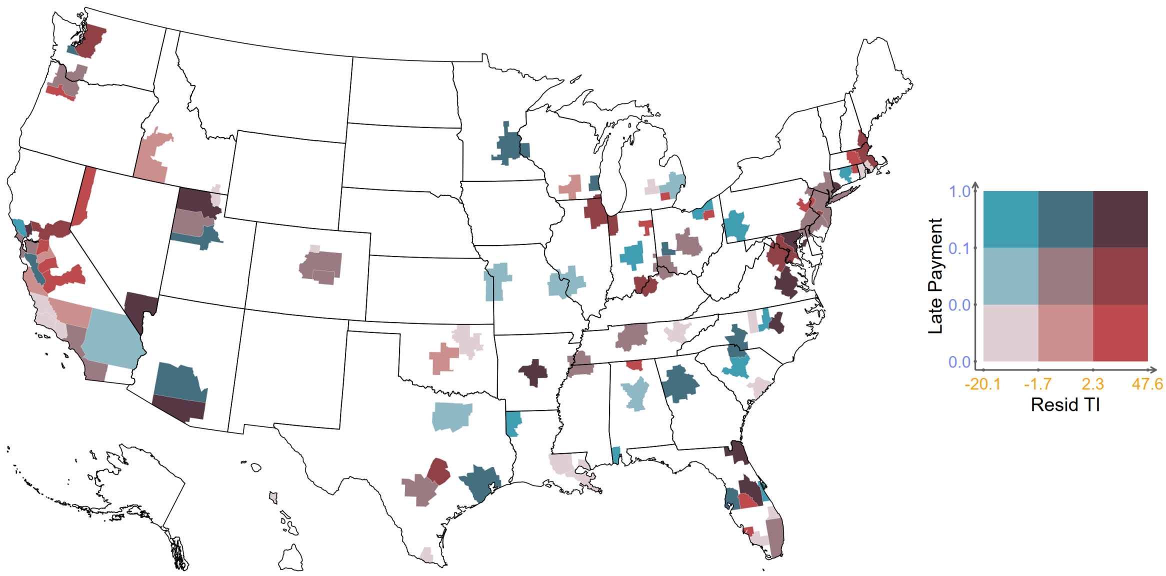
This figure shows the geographic distribution of the average TI residuals estimated from Equation 1 for the period from 1999Q4 to 2024Q3.

Figure 2: Late Payment



This figure shows the geographic distribution of the average likelihood of late payment for the period from 2000Q1 to 2024Q4.

Figure 3: Correlation between Late Payment and TI Residuals



This figure depicts the bi-variate geographic distribution of the correlation between the likelihood of late payment and lagged TI residuals for the period from 2000Q1 to 2024Q4.

Table 1: Summary Statistics for Equation 1

	N	Mean	Std.Dev.	25th pct	Median	75th pct
ti	192,352	12.809	25.435	0.000	0.000	15.000
fr	192,352	2.010	3.338	0.000	0.000	3.000
Transaction SQFT	192,352	13126.862	45479.483	1800.000	3962.000	10202.000
g_renew	192,352	0.260	0.439	0.000	0.000	1.000
classA	192,352	0.470	0.499	0.000	0.000	1.000
Building Size	192,352	346226.179	428524.731	83277.000	188129.000	427486.000
yrsincerenov	192,352	12.275	14.124	0.000	8.000	20.000
distance2CBD	192,352	12.423	13.996	1.764	6.525	18.339
public_landlord	192,352	0.301	0.459	0.000	0.000	1.000
public_tenant	192,352	0.073	0.261	0.000	0.000	0.000
large_tenant	192,352	0.735	0.441	0.000	1.000	1.000
new_lease	192,352	0.489	0.500	0.000	0.000	1.000
net_lease	192,352	0.223	0.416	0.000	0.000	0.000
post_covid	192,352	0.196	0.397	0.000	0.000	0.000

This table shows summary statistics (number of observations, mean, standard deviation, and 25th, 50th, and 75th percentiles) of key variables included in Equation 1 and additional indicators (e.g., publicly traded landlord) that capture heterogeneity in the impact of leasing investment on late payment, for the period from 1999Q4 to 2024Q3. Table A.1 defines all variables and lists all data sources.

Table 2: Coefficient Estimates for Equation 1

	(1)	(2)
	ti	fr
lntransactionsqft	4.463***	0.613***
	(5.55)	(5.01)
g_renew	-7.983***	-0.823***
	(-6.26)	(-5.70)
ClassA	5.281***	0.687***
	(9.31)	(9.98)
lnbldgsize	1.840***	0.171***
	(6.69)	(3.73)
yrsincerenov	-0.109***	-0.009***
	(-9.62)	(-4.09)
km_to_nid	-0.160***	-0.016***
	(-3.71)	(-3.74)
Constant	-43.960***	-4.991***
	(-5.07)	(-3.33)
MSA FE	Yes	Yes
YearQtr FE	Yes	Yes
R-squared	0.204	0.231
# Obs	192,352	192,352

This table shows the panel regression results from estimating Equation 1 over the period from 1999Q4 to 2024Q3. The dependent variable is tenant improvement allowance (ti) in column (1), representing the negotiated allowance provided by landlords for tenant renovations; and free rent (fr) in column (2), defined as the number of rent-free months in a lease. All other variables are defined in Table A.1. MSA and Year-Quarter fixed effects are included. Standard errors are clustered by MSA. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Summary Statistics for Equation 2

	N	Mean	Std.Dev.	25th pct	Median	75th pct
LatePmt	73,651	0.061	0.238	0.000	0.000	0.000
Dlq30plus	73,651	0.038	0.190	0.000	0.000	0.000
Dlq60plus	73,651	0.036	0.187	0.000	0.000	0.000
Dlq90plus	73,651	0.036	0.185	0.000	0.000	0.000
ti_resid	73,651	1.084	23.970	-13.396	-3.548	8.027
fr_resid	73,651	0.076	2.921	-1.702	-0.376	1.187
origloanbal (in 1,000 USD)	73,651	71307.369	119342.786	13650.000	37500.000	86500.000
ltv	73,651	67.212	118.431	53.150	64.520	74.110
dscrnoi	73,651	2.183	1.666	1.390	1.680	2.350
1(dscrnoi<securdscr)	73,651	0.696	0.460	0.000	1.000	1.000
actrate	73,651	5.757	10.346	5.000	5.640	6.150
occrate	73,651	90.652	7.924	87.500	92.607	95.953
Class A	73,651	0.592	0.492	0.000	1.000	1.000
Building Size	73,651	451629.955	514886.987	123226.157	271000.000	612050.850
yrsincerenov	73,651	12.269	13.328	1.000	9.000	19.000
Distance2CBD	73,651	8.109	10.755	1.165	4.418	9.807

This table shows summary statistics of key variables included in Equation 2 from 2000Q1 to 2024Q4. Variables and residuals derived from Equation 1 are lagged by one quarter; all other variables are measured contemporaneously. Table A.1 defines all variables and lists all data sources.

Table 4: Pairwise Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	LatePmt	ti_resid	fr_resid	origloanbal	ltv	dscrnoi	d_dscr_decrease	actrate	occrate	ClassA	buildingsize	yrsincerenov	Distance2CBD
LatePmt	1.00												
ti_resid	-0.02***	1.00											
	(0.00)												
fr_resid	-0.00	0.44***	1.00										
	(0.18)	(0.00)											
origloanbal	-0.03***	0.06***	0.03***	1.00									
	(0.00)	(0.00)	(0.00)										
ltv	0.05***	-0.00	0.00	0.04***	1.00								
	(0.00)	(0.25)	(0.68)	(0.00)									
dscrnoi	-0.07***	0.03***	0.00	0.13***	-0.06***	1.00							
	(0.00)	(0.00)	(0.52)	(0.00)	(0.00)								
1(dscrnoi<securdscr)	0.09***	0.01**	0.02***	0.07***	0.03***	-0.06***	1.00						
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)							
actrate	0.01***	-0.01**	-0.00	-0.03***	0.00	-0.03***	0.01***	1.00					
	(0.00)	(0.02)	(0.93)	(0.00)	(0.58)	(0.00)	(0.00)						
occrate	-0.10***	-0.01**	-0.06***	-0.01	-0.03***	0.09***	-0.06***	0.01***	1.00				
	(0.00)	(0.02)	(0.00)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)					
ClassA	-0.02***	0.02***	0.02***	0.15***	0.00	0.07***	-0.01*	-0.00	-0.06***	1.00			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.41)	(0.00)	(0.08)	(0.46)	(0.00)				
buildingsize	-0.05***	0.07***	0.07***	0.18***	-0.04***	0.04***	-0.00	-0.00	-0.06***	0.32***	1.00		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.68)	(0.19)	(0.00)	(0.00)			
yrsincerenov	-0.03***	-0.01**	-0.01***	-0.06***	-0.01***	0.02***	-0.04***	-0.02***	0.06***	-0.27***	-0.20***	1.00	
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
Distance2CBD	0.10***	-0.02***	-0.02***	-0.11***	0.03***	-0.08***	-0.02***	-0.00	0.01***	-0.07***	-0.25***	0.04***	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.53)	(0.00)	(0.00)	(0.00)	(0.00)	

This paper reports the correlation coefficients across *LatePmt*, a dichotomous variable that indicates any type of late payment, and variables included in Equation 2. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Coefficient Estimates for Equation 2

	(1)	(2)	(3)
	LatePmt	LatePmt	LatePmt
ti_resid	-0.017***		-0.014***
	(-3.09)		(-2.59)
fr_resid		-0.105*	-0.055
		(-1.86)	(-0.93)
lnorigloanbal	-0.863**	-0.862**	-0.859**
	(-2.48)	(-2.48)	(-2.47)
actrate	0.025***	0.025***	0.025***
	(8.56)	(8.60)	(8.61)
ltv	0.006	0.006	0.006
	(1.09)	(1.09)	(1.09)
dscrnoi	-2.027***	-2.046***	-2.029***
	(-3.54)	(-3.58)	(-3.54)
dscrnoi_sq	0.117***	0.118***	0.117***
	(2.88)	(2.91)	(2.88)
1(dscrnoi$<$securdscr)	1.562*	1.568*	1.566*
	(1.74)	(1.75)	(1.75)
occrate	-1.083***	-1.079***	-1.083***
	(-2.65)	(-2.64)	(-2.65)
occrate_sq	0.005**	0.005**	0.005**
	(2.08)	(2.06)	(2.08)
Class A	-0.129	-0.127	-0.131
	(-0.18)	(-0.18)	(-0.18)
lnbuildingsize	-0.265	-0.272	-0.263
	(-0.81)	(-0.83)	(-0.80)
yrsincerenov	-0.067**	-0.067**	-0.066**
	(-2.52)	(-2.52)	(-2.51)
Distance2CBD	0.136**	0.136**	0.136**
	(2.18)	(2.18)	(2.18)
yield	0.594*	0.608*	0.593*
	(1.88)	(1.91)	(1.87)
Constant	74.185***	74.162***	74.162***
	(4.48)	(4.48)	(4.49)
Originator	Yes	Yes	Yes
OrigYearMon	Yes	Yes	Yes
Orig State	Yes	Yes	Yes
Adj. R-squared	0.142	0.142	0.142
# Obs	73,651	73,651	73,651

This table shows the panel regression results from estimating Equation 2. The dependent variable is *LatePmt*, a dichotomous variable of any type of late payment associated with a loan in a given year-month. The independent variables are the lagged residuals pertaining to tenant improvement allowance (*ti_resid*) in column (1), free rent (*fr_resid*) in column (2), and both in column (3). All other variables are defined in Table A.1. Fixed effects pertaining to property type, originator, origination year-month, and origination state are included. Standard errors are clustered by originator and by origination state. *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Coefficient Estimates for Equation 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dlq30plus	Dlq30plus	Dlq30plus	Dlq60plus	Dlq60plus	Dlq60plus	Dlq90plus	Dlq90plus	Dlq90plus
ti_resid_std	-0.014***		-0.011***	-0.013***		-0.010**	-0.013***		-0.010**
	(-3.24)		(-2.65)	(-3.03)		(-2.58)	(-2.99)		(-2.55)
fr_resid_std		-0.112***	-0.075*		-0.098**	-0.062		-0.094**	-0.059
		(-2.59)	(-1.81)		(-2.29)	(-1.51)		(-2.22)	(-1.46)
lnorigloanbal	-1.134***	-1.131***	-1.129***	-1.111***	-1.108***	-1.106***	-1.106***	-1.104***	-1.102***
	(-3.84)	(-3.83)	(-3.83)	(-3.78)	(-3.77)	(-3.76)	(-3.78)	(-3.77)	(-3.77)
actrate	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.57)	(0.71)	(0.63)	(0.70)	(0.83)	(0.75)	(0.65)	(0.78)	(0.70)
ltv	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
	(1.13)	(1.13)	(1.13)	(1.13)	(1.13)	(1.13)	(1.13)	(1.13)	(1.13)
dscrnoi	-2.159***	-2.174***	-2.162***	-2.040***	-2.055***	-2.043***	-1.928***	-1.942***	-1.931***
	(-4.51)	(-4.53)	(-4.51)	(-4.34)	(-4.37)	(-4.35)	(-4.21)	(-4.24)	(-4.22)
dscrnoi_sq	0.131***	0.132***	0.131***	0.123***	0.124***	0.124***	0.116***	0.117***	0.116***
	(4.11)	(4.14)	(4.12)	(3.93)	(3.96)	(3.94)	(3.78)	(3.82)	(3.79)
1(dscrnoi<securdscr)	0.682	0.689	0.687	0.580	0.586	0.584	0.546	0.552	0.550
	(0.90)	(0.91)	(0.91)	(0.78)	(0.79)	(0.78)	(0.74)	(0.74)	(0.74)
occrate	-1.204***	-1.201***	-1.204***	-1.128***	-1.125***	-1.128***	-1.001***	-0.998***	-1.001***
	(-3.04)	(-3.03)	(-3.04)	(-2.94)	(-2.93)	(-2.94)	(-2.70)	(-2.69)	(-2.70)
occrate_sq	0.006***	0.006**	0.006***	0.006**	0.006**	0.006**	0.005**	0.005**	0.005**
	(2.59)	(2.57)	(2.59)	(2.51)	(2.49)	(2.50)	(2.26)	(2.25)	(2.26)
Class A	-0.711	-0.711	-0.714	-0.686	-0.686	-0.688	-0.677	-0.677	-0.679
	(-1.17)	(-1.18)	(-1.18)	(-1.14)	(-1.14)	(-1.14)	(-1.13)	(-1.13)	(-1.13)
lnbuildingsize	0.112	0.108	0.115	0.099	0.095	0.101	0.095	0.091	0.098
	(0.42)	(0.41)	(0.43)	(0.38)	(0.36)	(0.39)	(0.37)	(0.35)	(0.38)
yrsincerenov	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.09)	(-0.09)	(-0.09)	(-0.08)	(-0.08)	(-0.08)	(-0.07)	(-0.08)	(-0.07)
Distance2CBD	0.154***	0.154***	0.154***	0.156***	0.156***	0.156***	0.157***	0.157***	0.157***
	(2.69)	(2.70)	(2.70)	(2.75)	(2.76)	(2.76)	(2.77)	(2.78)	(2.78)
yield	-0.580***	-0.570***	-0.581***	-0.659***	-0.649***	-0.660***	-0.685***	-0.675***	-0.686***
	(-3.19)	(-3.13)	(-3.20)	(-3.70)	(-3.64)	(-3.71)	(-3.89)	(-3.83)	(-3.89)
Constant	76.246***	76.215***	76.215***	72.281***	72.255***	72.255***	66.627***	66.603***	66.603***
	(4.65)	(4.65)	(4.65)	(4.54)	(4.54)	(4.54)	(4.32)	(4.31)	(4.32)
Fixed Effects									
PropType	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Originator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
OrigYearMon	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Orig State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.203	0.203	0.203	0.204	0.204	0.204	0.203	0.203	0.203
# Obs	73,651	73,651	73,651	73,651	73,651	73,651	73,651	73,651	73,651

This table reports the regression results that are identical to those in Table 5, except we replace the dependent variable with indicators for late payment with at least 30, 60, and 90 days, respectively.

Table 7: Cross-Sectional Heterogeneity for Equation 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	LatePmt	LatePmt	LatePmt	LatePmt	LatePmt	LatePmt	LatePmt	LatePmt	LatePmt	LatePmt	LatePmt	LatePmt
Hetero	public_landlord	public_tenant	large_tenant	new_lease	net_lease	post_covid	public_landlord	public_tenant	large_tenant	new_lease	net_lease	post_covid
Residual	ti_resid	ti_resid	ti_resid	ti_resid	ti_resid	ti_resid	fr_resid	fr_resid	fr_resid	fr_resid	fr_resid	fr_resid
hetero_yes	-0.008	-0.013	-0.022***	-0.012**	-0.023**	-0.005	-0.115	0.150	-0.112*	-0.100*	-0.230*	-0.127*
	(-1.12)	(-1.28)	(-3.46)	(-2.04)	(-2.26)	(-0.74)	(-1.55)	(0.97)	(-1.77)	(-1.69)	(-1.73)	(-1.76)
hetero_no	-0.025***	-0.018***	-0.007	-0.029***	-0.015**	-0.023***	-0.098	-0.135**	-0.089	-0.115	-0.073	-0.096
	(-3.16)	(-3.07)	(-0.71)	(-3.15)	(-2.33)	(-3.29)	(-1.39)	(-2.47)	(-1.23)	(-1.44)	(-1.30)	(-1.41)
lnorigloanbal	-0.861**	-0.863**	-0.863**	-0.860**	-0.861**	-0.858**	-0.862**	-0.861**	-0.862**	-0.862**	-0.862**	-0.861**
	(-2.48)	(-2.48)	(-2.49)	(-2.48)	(-2.48)	(-2.47)	(-2.48)	(-2.47)	(-2.48)	(-2.48)	(-2.48)	(-2.48)
actrate	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***
	(8.57)	(8.57)	(8.50)	(8.53)	(8.58)	(8.49)	(8.61)	(8.61)	(8.60)	(8.60)	(8.59)	(8.60)
ltv	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)
dscrnoi	-2.022***	-2.027***	-2.024***	-2.025***	-2.025***	-2.034***	-2.046***	-2.052***	-2.046***	-2.046***	-2.047***	-2.045***
	(-3.53)	(-3.54)	(-3.54)	(-3.54)	(-3.54)	(-3.55)	(-3.58)	(-3.59)	(-3.58)	(-3.58)	(-3.58)	(-3.57)
dscrnoi_sq	0.116***	0.117***	0.117***	0.117***	0.117***	0.117***	0.118***	0.119***	0.118***	0.118***	0.118***	0.118***
	(2.86)	(2.88)	(2.87)	(2.88)	(2.87)	(2.88)	(2.92)	(2.93)	(2.91)	(2.91)	(2.92)	(2.91)
1(dscrnoi<securdscr)	1.573*	1.563*	1.561*	1.558*	1.568*	1.564*	1.567*	1.570*	1.568*	1.568*	1.568*	1.570*
	(1.76)	(1.74)	(1.74)	(1.74)	(1.74)	(1.74)	(1.75)	(1.75)	(1.75)	(1.75)	(1.75)	(1.75)
occrate	-1.085***	-1.083***	-1.086***	-1.083***	-1.082***	-1.088***	-1.079***	-1.080***	-1.080***	-1.079***	-1.076***	-1.078***
	(-2.66)	(-2.65)	(-2.66)	(-2.65)	(-2.65)	(-2.67)	(-2.64)	(-2.64)	(-2.64)	(-2.64)	(-2.63)	(-2.64)
occrate_sq	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**
	(2.09)	(2.08)	(2.09)	(2.08)	(2.08)	(2.10)	(2.06)	(2.06)	(2.06)	(2.06)	(2.06)	(2.06)
Class A	-0.129	-0.127	-0.120	-0.135	-0.132	-0.121	-0.128	-0.132	-0.128	-0.128	-0.129	-0.126
	(-0.18)	(-0.17)	(-0.16)	(-0.19)	(-0.18)	(-0.17)	(-0.18)	(-0.18)	(-0.18)	(-0.18)	(-0.18)	(-0.17)
lnbuildingsize	-0.272	-0.266	-0.265	-0.275	-0.267	-0.269	-0.272	-0.269	-0.273	-0.274	-0.273	-0.272
	(-0.83)	(-0.81)	(-0.81)	(-0.84)	(-0.81)	(-0.82)	(-0.83)	(-0.82)	(-0.83)	(-0.84)	(-0.83)	(-0.83)
yrsincerenov	-0.067**	-0.067**	-0.066**	-0.066**	-0.067**	-0.066**	-0.067**	-0.067**	-0.067**	-0.067**	-0.067**	-0.067**
	(-2.53)	(-2.52)	(-2.53)	(-2.52)	(-2.53)	(-2.51)	(-2.52)	(-2.53)	(-2.52)	(-2.52)	(-2.54)	(-2.52)
Distance2CBD	0.136**	0.136**	0.135**	0.136**	0.135**	0.136**	0.136**	0.136**	0.136**	0.136**	0.135**	0.136**
	(2.18)	(2.18)	(2.17)	(2.18)	(2.17)	(2.18)	(2.18)	(2.18)	(2.18)	(2.18)	(2.16)	(2.18)
yield	0.595*	0.594*	0.598*	0.601*	0.592*	0.597*	0.607*	0.613*	0.607*	0.608*	0.606*	0.608*
	(1.88)	(1.88)	(1.89)	(1.91)	(1.87)	(1.89)	(1.91)	(1.91)	(1.91)	(1.91)	(1.90)	(1.91)
Constant	74.309***	74.188***	74.288***	74.228***	74.169***	74.419***	74.159***	74.170***	74.202***	74.176***	74.119***	74.110***
	(4.50)	(4.48)	(4.49)	(4.49)	(4.48)	(4.50)	(4.48)	(4.48)	(4.48)	(4.48)	(4.48)	(4.48)
Fixed Effects												
PropType	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Originator	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
OrigYearMon	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Orig State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142
# Obs	73,651	73,651	73,651	73,651	73,651	73,651	73,651	73,651	73,651	73,651	73,651	73,651

This table reports regression results examining cross-sectional heterogeneity. The dependent variable, *LatePmt*, is a dichotomous indicator of any late payment associated with a loan in a given year-month. The independent variables are lagged residuals averaged across lease transactions within subsamples defined by five heterogeneity indicators: publicly traded landlord, publicly traded tenant, large tenant, new leases, and renewals. Specifically, *hetero_yes* averages the product of lease investment variables (i.e., *ti*, *fr*) and the respective heterogeneity indicator (e.g., *public_tenant*), while *hetero_no* aggregates the product of lease investment variables and one minus that indicator. All other variables are defined in Table A.1. Fixed effects pertaining to property type, originator, origination year-month, and origination state are included. Standard errors are clustered by originator and origination state. t-statistics are presented in parentheses, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Cross-Sectional Heterogeneity for Equation 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hetero	public_landlord	public_tenant	large_tenant	new_lease	net_lease	post_covid	public_landlord	public_tenant	large_tenant	new_lease	net_lease	post_covid
Residual	ti_resid	ti_resid	ti_resid	ti_resid	ti_resid	ti_resid	fr_resid	fr_resid	fr_resid	fr_resid	fr_resid	fr_resid
Panel A: Dlq30plus												
hetero_yes	-0.006	-0.015*	-0.016***	-0.008*	-0.017**	-0.007	-0.067	-0.124	-0.119**	-0.087*	-0.254**	-0.105*
	(-1.31)	(-1.68)	(-3.17)	(-1.74)	(-2.21)	(-1.32)	(-1.21)	(-1.55)	(-2.47)	(-1.93)	(-2.57)	(-1.89)
hetero_no	-0.022***	-0.014***	-0.011	-0.030***	-0.014**	-0.018***	-0.149**	-0.110**	-0.094	-0.151**	-0.075	-0.113**
	(-3.08)	(-3.13)	(-1.52)	(-3.62)	(-2.56)	(-3.00)	(-2.43)	(-2.44)	(-1.62)	(-2.42)	(-1.61)	(-2.24)
Panel B: Dlq60plus												
hetero_yes	-0.005	-0.014	-0.015***	-0.007	-0.016**	-0.006	-0.052	-0.119	-0.113**	-0.078*	-0.232**	-0.073
	(-1.11)	(-1.65)	(-3.04)	(-1.58)	(-2.16)	(-1.03)	(-0.92)	(-1.49)	(-2.34)	(-1.76)	(-2.38)	(-1.31)
hetero_no	-0.021***	-0.013***	-0.010	-0.028***	-0.013**	-0.017***	-0.136**	-0.096**	-0.060	-0.129**	-0.063	-0.106**
	(-2.96)	(-2.91)	(-1.33)	(-3.44)	(-2.36)	(-2.91)	(-2.24)	(-2.12)	(-1.03)	(-2.03)	(-1.34)	(-2.11)
Panel C: Dlq90plus												
hetero_yes	-0.005	-0.016*	-0.015***	-0.007	-0.014*	-0.006	-0.058	-0.108	-0.105**	-0.070	-0.200**	-0.081
	(-1.11)	(-1.86)	(-3.00)	(-1.45)	(-1.93)	(-1.03)	(-1.06)	(-1.39)	(-2.18)	(-1.58)	(-2.07)	(-1.54)
hetero_no	-0.020***	-0.013***	-0.009	-0.028***	-0.013**	-0.017***	-0.123**	-0.093**	-0.066	-0.131**	-0.067	-0.097*
	(-2.88)	(-2.83)	(-1.28)	(-3.49)	(-2.43)	(-2.87)	(-2.08)	(-2.08)	(-1.20)	(-2.16)	(-1.41)	(-1.94)

This table reports the regression results that are identical to those in Table 7, except we replace the dependent variable with indicators for late payment with at least 30, 60, and 90 days in Panels A, B, and C, respectively.

Table A.1: Variable Definitions

Variable	*Source*	*Definition*
Panel A: Lease level		
ti	CompStak	The negotiated allowance that the landlord is giving back to the tenant to renovate/improve the space leased, or the estimated value of such work in the case of pre-built spaces.
fr	CompStak	The number of months in a lease for which rent is not charged.
Transaction SQFT	CompStak	The amount of space (in square feet) leased by the tenant for the given transaction.
g_renew	CompStak	An indicator for lease renewals.
public_landlord	CompStak, S&P Global	An indicator for pubicly listed landlords. We classify a landlord as public if her property involved in the lease transaction matches any property owned by a publicly listed company in S&P Global.
public_tenant	CompStak	An indicator for pubicly listed tenants.
large_tenant	CompStak	An indicator equal to 1 if the count of employees the tenant company employs is above sample median and 0 otherwise.
new_lease	CompStak	An indicator for new leases.
net_lease	CompStak	An indicator for net lease types: Single Net, Double Net, or Triple Net.
post_covid		An indicator for dates after 2020Q1.
Panel B: Property level		
occrate	Trepp	Occupancy rate.
classA	CompStak	An indicator for Class-A buildings, or buildings with the highest desirability.
Building Size	CompStak	The size of the entire building.
propage	CompStak	The difference between the transaction year and the year in which building construction was completed.
yrsincerenov	CompStak	The difference between the transaction year and the year in which the building was most recently renovated.
distance2CBD	Holian and Kahn	Distance to the nearest central business district (in kilometer).
Panel C: Loan level		
LatePmt	Trepp	An indicator for any type of late payment with derived delinquency status codes other than 0 (current).
Dlq30plus	Trepp	Late payment with at least 30 days.
Dlq60plus	Trepp	Late payment with at least 60 days.
Dlq90plus	Trepp	Late payment with at least 90 days.
ti_resid	CompStak	TI residuals estimated from Equation 1.
fr_resid	CompStak	FR residuals estimated from Equation 1.
origloanbal (in 1,000 USD)	Trepp	Original loan balance.
ltv	Trepp	Securitization loan balance divided by most recent appraised value.
dscrnoi	Trepp	A ratio of net operating income (NOI) to debt service. Winsorized at the 1st and the 99th percentiles.
1(dscrnoi<securdscr)	Trepp	An indicator equal to 1 if current DSCR is lower than the DSCR upon securitization and 0 otherwise.
actrate	Trepp	Annualized gross rate used to calculate the current period scheduled interest amount.
yield	FRED St. Louis	Annualized yield on 10-year treasury securities.

This table shows variable definitions and data sources.

Table A.2: Balance Test

	(1)	(2)
	trepp_matched	trepp_matched
	ti_yes	fr_yes
leasing variable	-0.017**	-0.010
	(-2.12)	(-0.86)
lntransactionsqft	-0.031***	-0.032***
	(-4.33)	(-4.53)
g_renew	0.024**	0.024***
	(2.59)	(2.78)
ClassA	-0.063**	-0.064***
	(-2.57)	(-2.61)
lnbldgsize	0.080***	0.080***
	(5.73)	(5.67)
yrsincerenov	0.001***	0.001***
	(3.08)	(3.09)
km_to_nid	-0.006***	-0.006***
	(-3.99)	(-4.00)
Constant	-0.084	-0.074
	(-0.58)	(-0.51)
MSA FE	Yes	Yes
YearQtr FE	Yes	Yes
R-squared	0.144	0.144
# Obs	496,700	496,700

This table addresses potential selection bias in the baseline analysis. The dependent variable, *trepp_matched*, equals 1 if a lease transaction is included in the sample analyzed in the first two columns of Table 2 and 0 otherwise. Following Table 2, the independent variables are indicators for the presence of tenant improvement allowance (column 1) and free rent (column 2).