Tenant Riskiness, Contract Length, and the Term Structure of Commercial Leases*

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Abstract

This paper explores the connection between tenant riskiness, commercial lease length and the term structure of lease contracts. Theory shows that the possibility of default on a long-term lease generates a risk/lease-length connection. The empirical work uses a large CompStak lease dataset combined with tenant characteristics (including risk) from Dun & Bradstreet. Regressions show that lease length is inversely related to the D&B risk measures, as predicted, and that risky tenants pay a higher rent premium for long-term contracts than low-risk tenants. The presence of such tenants thus raises the slope of the term structure of commercial rents.

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1. Introduction

In commercial leasing, what determines whether a tenant signs a long-term or short-term contract? Relatively few papers in the leasing literature address this question. Those that do focus on a particular factor: the magnitude of "relationship-specific" investment, such as a restaurant's investment in specialized kitchen facilities. The expectation is that, when a large investment is needed, tenants will require a long-term lease that allows full exploitation of the investment. Papers that investigate this effect include Joskow (1987), who studies the coal industry, Brickley et al. (2006), who study franchising agreements, Bandiera (2007), who studies 19th century sharecropping, and Yoder et al. (2008), who study leases for grazing land.[1]

One goal of the present paper is to study commercial lease duration, but with a different focus. We are interested in the effect of a tenant's "riskiness" on the length of their lease contract, where riskiness is meant to capture the likelihood of default on the contract, which entails a loss of revenue for the landlord. With default risk likely to militate against a long-term lease, where default has more chance of occuring, we expect contract duration to decrease with the tenant's riskiness. Motivated by a theoretical model, our empirical investigation of this connection uses data on individual leases along with tenant characteristics, relying on a firm-level risk measure developed and marketed by Dun & Bradstreet (D&B) as our primary indicator of tenant risk. The D&B risk measure is designed to highlight the likelihood that a company may fail to pay its bills in the next year and serves as a proxy for tenant default risk. That and other information in the D&B database are merged with our lease data at the establishment level and yield a unique data file that makes the empirical analysis in this paper possible. Our estimating sample includes over 125,000 records, each with a rich set of tenant attributes (age, industry, etc.) and features of their

[1] A related paper Crocker and Masten (1988) focuses on regulatory impacts on contract duration. In a different vein, Titman and Twite (2013) study the connection between lease duration and a country's legal structure (common vs. civil law), which affects dispute resolution. Another empirical focus is on the duration of union labor contracts, as in Gray (1978).

lease contracts (lease length and rate, space leased, new lease versus renewal, etc.), in addition to location down to the building level.[2]

While the conceptual connection between tenant riskiness and rental contract length seems intuitive, we seek stronger grounds for our hypothesis by developing a theoretical model that explores this connection. The model is centered around the possibility of default on a rental contract, and to best of our knowledge, it is the only theoretical framework in the literature to link potential default and rental contract length.[3] The model's default focus also creates a link to the sizable literature on mortgage default, especially to papers where default affects the type of mortgage contract chosen (analogous to contract length in the present context).[4]

Our highly stylized model has two periods, denoted 0 and 1, and two possible contract terms. Under short-term (ST) contracts, the rent paid is different in each period, while under a long-term (LT) contract, the rent is set at the same level in both periods. Tenants live for two periods (0 and 1) and they rely on either a sequence of two ST contracts or a single LT contract. Though random, revenue is uniformly higher for the "good" tenant type than for the "bad" type. For an assignment of tenants to contracts to be sustainable when both ST and LT contracts are realistically used, neither tenant type should be able to earn a higher profit by switching to the other contract type, given the prevailing rents. We show that, under a particular set of assumptions on how rents on contracts are set, the assignment of bad tenants to ST contracts and good tenants to the LT contract is sustainable.

In an important connection to this paper, the finance literature has extensively investigated the link between borrower riskiness and the term of debt contracts, which somewhat parallels the link between tenant riskiness and lease length. The seminal theoretical paper is by Diamond (1991), and it spurred substantial addition research. Diamond shows that the relationship between tenant riskiness and debt maturity is nonmonotonic, with high- and low-risk borrowers using short-

[2] Financially unreliable tenants may also have less predictable future space needs than low-risk tenants, which could further reduce their tendency to sign long-term contracts. However, because the Dun & Bradstreet risk measures are constructed to highlight the possibility that a company may not pay its bills, we believe that evidence based on those measures captures the influence of default risk as the more salient consideration. Other features of our empirical approach described later in the paper also help to separate out the effect of predictability of future space needs.

[3] Harris and Holmstrom (1987) and Poutvaara et al. (2017) propose theoretical lease-length models that apply to other contexts beside commercial leasing.

[4] For papers on mortgage default, see Kau, Keenan and Kim (1993, 1994), Riddiough and Thompson (1993), Brueckner (2000), Foote, Gerardi, and Willen (2008), Mian and Sufi (2009), and Guiso, Sapienza and Zingales (2013), among others. The interaction between default and mortgage choice is studied by Posey and Yavas (2001), Campbell and Cocco (2003), and Brueckner, Calem and Nakamura (2016).

term debt and medium-risk borrowers using long-term debt. This result, which contrasts to the prediction of a monotonic inverse relationship between riskiness and contract length in the current model, is due to a variety of differences between debt and lease contracts.

As in the case of interest rates, lease contracts also have a term structure, with the initial rent on a lease expected to increase with length of the contract. As shown in the seminal option-based models of Grenadier (1995, 2005), the expected future path of short-term lease rates influences the lease term structure in a positive direction, in the same way that the path of future short-term interest rates influences the interest-rate term structure. Thus, a rising path of short-term rents can lead to an "upward-sloping" rental term structure.[5] Although our paper mainly focuses on lease length, a secondary purpose, made possible by our unique data set, is to investigate the effect of tenant riskiness on the slope of the lease term structure.

Such a connection may exist because, in addition to default, a further concern of the landlord in writing a long-term lease is a greater scope for misbehavior of the tenant given the length of the contract. This misbehavior can include late rent payments and other disruptions, along with the possibility of default, all of which are less of a concern under short-term contracts. The landlord must again be compensated for the greater chance of such events via a higher initial rent. Such misbehavior, depends on the riskiness of the tenant, which is the driver of the lease-length analysis just described. While the observed term structure of rents will thus depend on the "average" riskiness of tenants, it is possible to unbundle this average effect by estimating term structures that apply to different tenant types. For reasons just described, our expectation is that the slope of the term structure for risky tenants is steeper than the slope for low-risk tenants, indicating a higher rent premium for long-term contracts when the tenant is risky.[6] Following our empirical analysis of tenant riskiness and lease length, we also briefly present evidence in support of this connection between tenant riskiness and the term structure.

Although Grenadier (1995, 2005) omits the effect of tenant riskiness in his term structure analysis, the related option-based models of Ambrose and Yildirim (2008) and Agarwal et al.

[5] While this linkage can be weakened through escalator clauses, which are commonly used and often cause rent to rise at a fixed percentage rate over the lease term, inflation *risk* is an additional concern affecting the rental structure. Uncertainty over future inflation creates uncertainty in the real value of fixed future rent payments over the lease term, for which the landlord must be compensated by a higher initial rent even in the presence of an escalator clause.

[6] Despite our theory's stark prediction that risky tenants never use long-term contracts, reality will only show a tendency in this direction, and the previous logic says that, when risky tenants take such contracts, they will pay a higher rent premium than low-risk tenants.

(2011) include it. Both of these papers, which make important contributions to the term-structure literature, show a positive effect of tenant riskiness on the rental term structure via numerical simulation, consistent with the previous intuition. A contribution of our empirical evidence is thus to provide empirical evidence in support of this important theoretical prediction of Ambrose and Yildirim (2008) and Agarwal et al (2011).[7]

Our empirical work on the term structure is also connected to previous research on the determinants of horizontal and vertical rent patterns in commercial buildings.[8] Using roughly 100 tall commercial buildings spread across U.S. cities, Liu, Rosenthal and Strange (2018) confirm the importance of both horizontal and vertical drivers of commercial lease rates, including effects from nearby agglomeration economies, street access, and height-related amenities. But that paper does not consider tenant riskiness. Using 2,482 lease transactions for commercial, industrial and agricultural properties, the empirical work of Agarwal et al. (2011) links the term structure of leases to the tenant's capital structure, including debt and capital assets as well as asset volatility, testing a prediction of their theoretical model. But the connection between term structure and tenant riskiness, another model prediction, is not actually tested. While Agarwal et al. (2011) use measures of tenant debt and assets that are not available in our data, their ability to control for horizontal and vertical drivers of rent are limited relative to ours. Some of our rent models, for example, include building-level fixed effects that capture innumerable nearby attributes of a commercial building's neighborhood in addition to building-specific quality and competition for space in the building, while additonal controls capture vertical rent patterns and the effects of other attributes of a rental suite.

The lease data used in the study are proprietary and were obtained from CompStak Inc., a commercial real estate data firm. Although many lease characteristics are available, we focus on the lease term as well as control variables such as amount of floor space leased.[9] As noted above, these data were matched at the establishment level with tenant information from D&B.[10] The D&B

[7] See Gunnelin and Soderberg (2003) and Bond et al. (2008) for other empirical studies of the rental term structure.
[8] See also Rosenthal, Strange and Urrego (2022) for a more expansive analysis of commercial rent gradients associated with distance to city centers and access to rapid transit.
[9] CompStak data were also used by Liu, Rosenthal and Strange (2018) to study vertical rent patterns in tall commercial buildings and by Rosenthal, Strange and Urrego (2022) to study the effect of the COVID-19 pandemic on horizontal (spatial) patterns of commercial rents.
[10] Recent papers that use D&B establishment-level data include Liu, Rosenthal and Strange (2024), who examine evidence of anchor establishment spillovers within and outside of buildings on the same city block, and Rosenthal and Strange (2020) who consider evidence on how closely situated companies must be to benefit from proximity to other establishments.

files provide a wealth of establishment-specific information, including type of company (we use SIC classification), age of the establishment, and most important for this study, the risk associated with doing business with the establishment, defined by D&B as the risk that the establishment may fail to pay its bills.[11] The D&B data were accessed through the Syracuse University library, which has a site license.

To anticipate, our estimates confirm that multiple factors affect lease length. Leases are always longer when more space is leased. That pattern suggests that transaction costs, including relocation costs for the tenant and contracting costs for the landlord, increase with space leased, ensuring that leases for more space have longer duration. Also, businesses that place greater weight on consumer awareness of the establishment's location have longer leases. This consideration is manifested in long observed leases in the retail sector, where a stable location matters for repeat customer visits, and shorter leases in manufacturing, where establishments receive comparatively infrequent on-site customer flow. Most importantly, controlling for these and other factors, lower-risk tenants have longer leases, consistent with our model. This pattern is especially apparent for tenants who are new to a building but is less relevant for lease renewals. Landlords have substantial idiosyncratic information on tenants seeking to renew a lease, making D&B's risk assessment less useful, while that assessment matters more for new tenants, which is what we find. Analogous patterns are also obtained based on tenant age, with the D&B risk measures having strong effects on lease length for younger companies but little effect for established companies (over 10 years in age). For these tenants, landlords would have considerable information without needing to rely on the D&B risk assessment.

Our term-structure analysis builds on the previous results, using regressions that relate rent per square foot to the lease term, which is now an independent rather than a dependent variable. Controlling for nearby and building-specific attributes, we run a series of regressions in which lease length is interacted with low-risk status and additional more expansive models in which separate regressions are run for low-risk and risky tenants (those in the D&B medium and high-risk categories). These latter models are heavily parameterized as they implicitly interact a tenant's

[11] The Dun & Bradstreet measure of establishment risk is based on company type, age of the establishment, whether the company is presently subject to lawsuits, liens or judgements, the company's net worth, and trade data. To anticipate, we work with a version of the D&B risk measure coded to three categories, low risk, medium risk and high risk.

risk classification with over 1,000 location fixed effects (zip-code or building level depending on the model) in addition to all of the other model controls. In all of the model specifications, and as in previous papers, we confirm an upward-sloping term structure, with higher lease rates on longer leases. New in this paper, we also confirm that the term-structure slope is flatter for low-risk tenants, who pay a smaller premium for a long-term contract than do risky tenants. The results thus suggest that tenant riskiness is a driver of the observed average term structure of commercial rents, which blends long-term rent premia across tenant types.

The plan of the paper is as follows. Section 2 presents the theoretical model, and section 3 discusses the data. Section 4 presents our empirical results on lease length, and section 5 present the term-structure results. Section 6 offers conclusions.

2. A theoretical model

2.1. The setup

In the model, both tenant types (good and bad) are risk neutral and live for two periods. We focus on a single cohort of tenants who begin life in period 0. Both tenant types earn the same revenue p_0 in period zero, while incurring no other cost aside from rent. In period 1, tenant type i earns revenue of $p_1^i = p_0 + \omega^i$, for $i = g, b$ (good, bad), where ω^i is a type-specific random variable. This random variable has an expected value k^i for type i, with these values satisfying $k^g > k^b$ but otherwise unrestricted in sign. Both k values could be negative, for example, in a business downturn. The remaining random portion of ω^i, denoted by ϵ, captures economy-wide shocks and is thus common to both types, so that $\omega^i = k^i + \epsilon$, with $E(\epsilon) = 0.$ The density and cumulative distribution function for ϵ are denoted $f(\cdot)$ and $F(\cdot)$, respectively, and the support of f is $[\underline{\epsilon}, \overline{\epsilon}]$.

Thus, the k^is determine the general level of type i's random period-1 revenue, and good tenants, with their high k value, are then less "risky" in the sense of having more favorable future revenue prospects. While riskiness is often gauged by a difference in variances, the variance of revenues in this setup is the same for both tenant types as a result of the common ϵ. But, as will be seen, the difference in the *levels* of random returns across the types (a result of different k^is) makes the bad type more likely to default on a long-term contract and thus riskier than the good type from the default perspective.

On the supply side, one or more landlords is present, each of whom owns multiple, long-lived rental properties, with each property rentable to either type of tenant. We analyze landlord interactions with our single cohort of tenants, recognizing that overlapping cohorts (one born, for example, in period 1 instead of 0) have identical experiences.

As in any analysis of contracting, the levels of both short-term (ST) and long-term (LT) rents in the model must be pinned down in some fashion. A common approach would be to assume that landlords earn zero profit from both contract types, corresponding to an assumption of perfect competition in leasing. With our two-period model, as explained below, this approach is not workable because default may then occur under both contract types rather than just under LT contracts, obscuring the issues we wish to explore. We pin down the level of rents by instead assuming a less competitive leasing environment. First, we assume that short-term rent in each period is set to extract all tenant revenue. Since revenue differs by type in period 1, ST rents will differ by type as well in that period, although period-0 rents are the same across types. Second, to ensure that both ST and LT contracts are offered, we assume that the rent level for a long-term contract takes a value that yields the same expected present value (EPV) of landlord profit as a sequence of ST contracts, conditional on the assignment of tenants to contracts. Conditional on this assignment, a landlord then is indifferent between the two contract types, preventing an outcome where only one type is provided. This equal-profit assumption is similar in spirit to the competitive assumption that the EPV of profit is zero for each contract type.

It is important to note that, rather than assuming a rent benchmark based on total revenue extraction for ST contracts, we could subtract some constant from the resulting ST rent levels in the two periods, reducing the landlord's EPV of ST profit, with LT rent set to also generate this lower profit level. This adjustment, which would have no effect on the results of the analysis, would allow for different degrees of competitiveness in the leasing market, better approximating conditions where landlord market power is limited. In the empirical work later in the paper, leasing competitiveness likely differs across cities and neighborhoods in our sample. Consistent with the discussion above, the effect of location-specific differences in competition on leasing outcomes is captured by the locational fixed effects in our regressions, including city, zipcode and building-level fixed effects.[12]

[12] An example of an environment with limited leasing competition is the one prevailing in Irvine, California, where one of the authors lives and works. The Irvine Company is a monopoly landlord that controls almost all of the

Because the rent on ST contracts adjusts to the fortunes of the tenants, yielding zero tenant profit in both periods, default on ST contracts does not occur. But since rent is set in advance under an LT contract, period 1 revenue can fall short of the rent level, leading to default. Therefore, our assumptions provide a convenient setting in which to analyze default risk as a factor driving the assignment of good and bad tenants across contract types.

Formally, let r_0 and r_1 denote the ST rents in the two periods, rent in period 0 is set equal to tenant revenue p_0, with $r_0 = p_0$ yielding zero profit for both tenant types. In period 1, $r_1^i = p_0 + k^i + \epsilon,\ i = g, b$, where ϵ is the realization of the common random term. Period-1 rents again reduce tenant profit to zero, but they now differ by type. With tenant ST profit thus equal to zero in both periods, the EPV of ST profit across the periods is also zero for both tenant types.

While default on ST contracts does not occur, default on an LT contract may occur if a tenant's period-1 revenue is low. To see how, let r denote the LT rent, which prevails in both periods. Then, for a type-i tenant, period-1 default occurs when revenue is less than r, or $p_0 + k^i + \epsilon < r$. Equivalently, default occurs when $\epsilon < r - p_0 - k^i$. Note that the tenant defaults even when he could cover a portion, but not all, of the LT rent, indicating that renegotiation of rent to secure a reduction is ruled out. In addition, this behavior shows that tenants do not have "deep pockets," since otherwise they use such funds to make up the shortfall.

Recognizing the possibility of default, the type-i tenant's EPV of profit under an LT contract is

$$\pi_{LT}^i(r) \ = \ p_0 \ - \ r \ + \ \delta \int_{r-p_0-k^i}^{\overline{\epsilon}} \big(p_0 + k^i + \epsilon - r\big) f(\epsilon) d\epsilon$$

$$= \ (1 + \delta(1 - F^i))(p_0 - r) \ + \ \delta(1 - F^i)k^i + \delta \int_{r-p_0-k^i}^{\overline{\epsilon}} \epsilon f(\epsilon) d\epsilon, \quad i = b, g, \qquad (1)$$

where δ is the discount factor, $F^i \equiv F(r - p_0 - k^i)$ for $i = b, g$, and the dependence of profit on r is noted. Note that the integral runs over the ϵ range where default does not occur ($r - p_0 - k^i \leq \epsilon \leq \overline{\epsilon}$). When default instead happens, it is assumed that the tenant goes out of business, paying no rent and earning no revenue (with period-1 profit thus equal to zero).[13] In addition to

commercial and residential rental property in the city, having built and sold owner-occupied housing using the remaining land in the city (which is now nearly fully built out). As noted above, however, and discussed further later in this section, the core patterns from our theory and subsequent empirical work are robust to differing degrees of local competition which, as an approximation, primarily affects the level of landlord profit.

[13] We can imagine that the landlord locks the doors to the leased space in response to a default, making it impossible for the tenant to earn revenue.

the absence of renegotiation, the tenant is also assumed to be unable to relocate in period 1 to another property offering an (affordable) ST contract.

We wish to analyze an outcome where one tenant type uses ST contracts and the other uses the LT contract, so that both contract types are realistically observed. The presence of both contract types is ensured by our assumption that LT rents (perhaps as a result of regulation) are set to make ST and LT contracts equally profitable for the landlord, given the identities of tenants that use them. To formalize this condition, analysis of landlord profit is required.

Like tenants, landlords are risk neutral. Letting c denote the landlord's cost per period, the EPV of landlord profit under ST contracts with a type-i tenant equals

$$\Pi_{ST}^{i} = r_0 - c + \delta\left(r_1^i - c\right) = (1+\delta)(p_0 - c) + \delta k^i, \quad i = \mathrm{b}, g, \tag{2}$$

where $r_0 = p_0$, $r_1^i = p_0 + k^i + \epsilon$, and $E(\epsilon) = 0$ are used. Note that the landlord's discount factor is assumed to be the same as the tenant's, equal to δ. To ensure that ST landlord profit is nonnegative in both periods, $p_0 \geq c$ and $p_0 + k^i + \underline{\epsilon} \geq c$ are assumed to hold, with the latter inequality ensuring $r_1^i \geq c$ regardless of the magnitude of ϵ.

When the LT contract is used by a type-i tenant, the EPV of landlord profit is given by

$$\Pi_{LT}^{i} = r - c + \delta \int_{r-p_0-k^i}^{\overline{\epsilon}} (r-c) f(\epsilon) d\epsilon - \delta \int_{\underline{\epsilon}}^{r-p_0-k^i} c f(\epsilon) d\epsilon. \tag{3}$$

Note that $r - c$ is earned in period 0 and in period 1 over the ϵ range where the type-i tenant does not default, whereas no revenue is earned under default while the cost c is still incurred.[14] This latter outcome assumes that the property cannot be immediately rented out after a tenant defaults (for example, the tenant may not immediately vacate the space). Simplifying, (3) equals

$$\begin{aligned} \Pi_{LT}^{i} &= r - c - \delta c + \delta r\left(1 - F\left(r - p_0 - k^i\right)\right) \\ &= (1+\delta)(r-c) - \delta r F\left(r - p_0 - k^i\right). \end{aligned} \tag{4}$$

Note that $r > c$ must hold for (4) to be nonnegative.[15]

[14] In the model of Ambrose and Yildirim (2008), the landlord can recover some portion of the revenue from the property under default.

[15] Observe that (1), (3) and (4) reflect the assumption $\underline{\epsilon} < r - p_0 - k^i$, so that default occurs over the ϵ range defined

2.2. Analysis of tenant assignments to contracts

For a fixed value of r, the good tenant earns higher profit than the bad tenant under the LT contract. To see this conclusion, suppress the i subscript in (1) so that it refers to a generic tenant. Differentiating this profit expression with respect to k using Leibniz's rule yields

$$\frac{\partial \pi_{LT}(r)}{\partial k} \;=\; \delta \int_{r-p_0-k}^{\overline{\epsilon}} f(\epsilon)d\epsilon \;>\; 0, \tag{5}$$

noting that the derivative with respect to the lower limit of integration equals zero given the default condition. With the derivative positive, it follows that the good tenant earns a higher present value of LT profit than the bad tenant holding r fixed, reflecting higher period-1 profit in the no-default state, a consequence of $k^g > k^b$. While this result suggests that good tenants will value the LT contract by more than bad tenants (who then would use ST contracts), that conclusion is premature. The reason is that the LT rent will depend on the allocation of tenant types across the contracts, so that holding r fixed in (5) is inappropriate.

To take this dependence into account, suppose that good (bad) tenants are assigned to LT (ST) contracts, as conjectured above. For landlords to earn the same EPV of profit from the two contracts given this assignment the condition

$$\Pi_{ST}^{b} \;=\; \Pi_{LT}^{g} \tag{6}$$

must hold, where the LHS is landlord ST profit when the tenant type is bad and the RHS is landlord LT profit when the tenant type is good. Using (2) and (4) and letting $\Delta\Pi \equiv \Pi_{LT}^{g} - \Pi_{ST}^{b}$ be the LT-ST landlord profit difference under the given assignment, the condition in (6) reduces to

$$\Delta\Pi \;=\; (1+\delta)(r-p_0) \;-\; \delta r F(r-p_0-k^g) \;-\; \delta k^b \;=\; 0. \tag{7}$$

The condition in (7) determines r as an implicit function of the parameters of the model. This solution is based on the initial assumption that ST rents extract all tenant revenue, which then determines a landlord's ST profit for a given tenant type, providing the benchmark for

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by this inequality. Recalling that nonnegative landlord ST profit in period 1 requires $p_0 + k^i + \underline{\epsilon} \geq c$ or $\underline{\epsilon} \geq c - p_0 - k^i$, the consistency of these requirements must be checked, as follows. Since (4) implies $r > c$ (a consequence of $F(r - p_o - k^i) > 0$ or $\underline{\epsilon} < r - p_0 - k^i$), it is possible for the inequalities $\underline{\epsilon} < r - p_0 - k^i$ and $\underline{\epsilon} \geq c - p_0 - k^i$ to both be satisfied, so that default occurs for low values of ϵ while landlords earn positive ST profit in period 1.

determination of the LT rent that equalizes landlord profit across the contract types under the assumed tenant assignment.

Let the r solution from (7) be denoted r^g to indicate that the good type is assumed to use the LT contract. Observe that if $k^b > 0$, so that the expected period-1 revenue for the bad tenant (and hence for the good tenant as well) is higher than period-0 revenue, then (7) requires $r^g > p_0$. Rent under the LT contract thus exceeds p_0, the period-0 ST rent, so that rents then have an upward-sloping term structure. The reason is that r must cover the landlord's loss when default occurs as well as compensating for the high (and forgone) expected ST rent that results from $k^b > 0$.[16]

Using (7) along with a stability argument, the appendix shows $\partial r^g/\partial k^g < 0$ and $0 < \partial r^g/\partial k^b < 1$, information that is useful below. While the first two inequalities in these statements hold generally, the third inequality holds when a natural sufficient condition is satisfied. To understand the first inequality, note that since a higher k^g reduces default, making the LT contract more attractive to landlords, r^g must fall to maintain equality of profit between the two contract types. Conversely, since a higher k^b makes the ST contracts more attractive, r^g must rise to maintain profit equality.

For the assumed allocation of tenants to contracts to be sustainable, neither tenant must have an incentive to switch to the other contract, viewing the rents charged as parametric. If the good tenant were to switch to the ST contracts, he would expect to pay the same zero-profit period-0 rent as the current bad tenant (equal to p_0) and would expect to also earn zero profit in period 1, with the EPV of profit thus equal to zero. For a switch to be undesirable, it must then be true that

$$\pi_{LT}^{g}(r^g) \geq 0, \tag{8}$$

using (1). In other words, the good type's EPV of profit under the LT contract, with the rent set conditional on the presence of the good type, must be zero or positive, thus being at least as large as the zero EPV of profit under the ST contracts. In addition, for the bad type to have no incentive to switch away from the zero-profit ST contracts, his EPV of profit under the LT contract given the prevailing rent r^g must be negative or zero:

[16] Note that, even though rent then exceeds revenue in period 0, the incentive for default is absent as long as the tenant's EPV of profit under the LT contract is positive. By contrast, default in period 1 depends only on a comparison of current rent and revenue since there is no subsequent period to consider.

$$\pi_{LT}^{b}(r^{g}) \;\; \leq \; 0. \tag{9}$$

The conditions (8) and (9) are not guaranteed to hold, but they are satisified, respectively, when k^g is sufficiently large and k^b is sufficiently small, yielding a large gap between the period-1 revenues of the tenant types:

Proposition 1. *The assignment of good tenants to the long-term contract and bad tenants to short-term contracts occurs when the tenants' period-1 revenues diverge sufficiently, with k^g and k^b sufficiently large and small, respectively.*

The proposition is established by first showing that (8) holds when k^g is large. Since $\partial r^g/\partial k^g < 0$ holds from above, $r^g - p_0 - k^g$ decreases as k^g rises, eventually falling below $\underline{\epsilon}$. The possibility of rent default by the good tenant then disappears (see the integrals in (3)), allowing π_{LT}^{g} from (1) to be written as[17]

$$\pi_{LT}^{g}(r^{g}) \;\; = \;\; \Delta\Pi \; + \; \delta(k^{g} - k^{b}) \; > \; 0 \tag{10}$$

using $\Delta\Pi = 0$ from (7), which validates (8). By continuity, (10) will also hold when k^g is large but not large enough to eliminate the possibility of default.[18]

To show that (9) holds when k^b is sufficiently small, observe that the inequalities $0 < \partial r^g/\partial k^b < 1$ from above imply that $r^g - p_0 - k_b$ decreases with k^b, thus eventually rising above $\overline{\epsilon}$ as k^b falls. With default by a bad tenant paying r^g then becoming certain, $\pi_{LT}^{b}(r^g) < 0$ follows, validating (9).[19] As before, continuity implies that this inequality will also hold when k^b is small but not small enough to make default certain.

The upshot is that when k^g is sufficiently large and k^b sufficiently small, assignment of the good (bad) tenants to LT (ST) contracts is the outcome generated by the model. Both tenant types have no incentive to switch between contracts. As mentioned in the introduction, the intuition underlying this assignment is that, with default protecting the tenant from the downside of low

[17] The F terms in (1) and (7) then become zero and the integral in (1) becomes $E(\epsilon)$, allowing π_{LT}^{g} to be rewritten as the expression in (10), using (7).

[18] Note that under the modification discussed in footnote 5, the RHS of (10) would equal $\delta(k^g - k^b)$, not zero, and the equation would hold as an equality, not as a strict inequality. The maintained allocation of tenants to contracts would thus still be an equilibrium under this modification.

[19] F^b in (1) then equals 1 and the integral is zero, so that $\pi_{LT}^{b}(r^g) = p_0 - r^g$. But since (7) implies that $(1+\delta)(p_0 - r^g)$ equals the three remaining negative terms in the equation, $\pi_{LT}^{b}(r^g) < 0$ follows.

period-1 profit while fixed rent allows enjoyment of the favorable upside, the good tenant (for whom the upside is bigger) values the LT contract more than does the bad tenant.

The preceding analysis shows that different future revenue prospects for tenants may lead them to favor different contract terms. While this conclusion has been illustrated under a particular strong set of assumptions, the lesson may be more general, and it can be used to motivate empirical work exploring the effect of tenant characteristics, including a riskiness measure, on the choice of rental contract terms.[20]

Even though landlords have been assumed to know tenant types, the assignment characterized in Proposition 1 would still emerge if tenant types were unobserved, being private information. In other words, with the LT rent set at r^g and ST rents set to extract all revenue from the bad type, the tenants would self-select across contracts in the manner described in the proposition. In this sense, the model bears some resemblance to models in the tradition of Rothschild and Stiglitz (1976), where the buyers have different risk levels and make quantity decisions, such as the amount of insurance to buy or the size of a mortgage loan (as in Brueckner (2000)). While asymmetric information distorts the choice of the low-risk buyer in these models, our model has no analogous quantity choice but instead just involves the choice of a contract type, thus lacking any similar distortion. In addition, while a zero-profit constraint is imposed on sellers in these models, we pin down the level of rents through our particular set of assumptions.

3. Data, sample design and summary statistics

Our matched record datafile is unique and extraordinarily comprehensive, making this study possible. The data provide detailed establishment-level information on lease and tenant

[20] In place of our maintained assumptions, suppose that perfect competition existed among multiple landlords, driving the EPV of profit to zero for each contract type in conventional fashion. Then ST rents would equal the land's cost c. As explained earlier, to ensure default does not occur under ST contracts, as in the existing model, the rent level c must be affordable under all circumstances, so that $p_0 > c$ and $p_0 + k^i + \underline{\epsilon}$ (the lowest possible type-i revenue in period 1) is larger than c. However, if LT rent also equals c, then it is easy to see that default is also absent under LT contracts, which then generate zero profit. The reason is that the lower limit of integration in the first integral in (30) equals $c - p_0 - k^i$, which is less than $\underline{\epsilon}$ by the previous inequalities, thus being outside the range of ϵ. The set of ϵ values leading to default is then empty, which also makes the last integral in (3) equal to zero, and the result is a zero value for (3) given $r = c$. Therefore, the absence of default under zero-profit ST contracts implies its absence as well for zero-profit LT contracts where $r = c$. Whether other zero-profit LT contracts exist where $r > c$ (and default may occur) is unclear. But the absence of default in the natural zero-profit LT case where $r = c$ shows the obstacles to generating a useful model under conventional assumptions.

attributes for establishments spread across a large number of cities. This section describes the rich features of the data used along with its limitations, and then reviews summary statistics.

3.1. Matched sample composition and design

As highlighted earlier, we use an establishment-level matched sample to conduct our analysis. For these purposes, lease data were obtained from CompStak Inc. while establishment attributes were obtained from Dun & Bradstreet. Data from the two files were matched using tenant street address, latitude and longitude, and tenant name, information that is available in both CompStak and D&B.[21]

The Dun & Bradstreet data were obtained through the Syracuse University library, which has a site license. The data were downloaded in 2018 for select areas of the United States and provide near complete coverage of companies present in a given location in that year. Data were obtained for Boston, the major cities in California, Chicago, the Washington DC MSA, northern New Jersey, New York City and Philadelphia. Restricting the D&B sample to records for which establishment age and employment at the site are both reported, the D&B records before matching with the CompStak file include 8.58 million establishments with combined employment of roughly 42.5 million workers.

The lease data are proprietary and were drawn from the CompStak database in October 2021. These data originate from commercial real-estate agent files as part of a sharing arrangement between commercial agents and CompStak. Agents are allowed to draw information on comparables from the CompStak database when working with clients seeking space. In exchange, agents share information on some of their previously arranged leases, which goes into the CompStak database. For the same areas as covered by the D&B data above, in total we obtained 615,784 lease records, although only 602,408 report lease length.

Given the nature of the two data files, some features of the matched sample are important to note. Most obviously, the CompStak records cover only a small portion of leases held by companies in a given location. This limitation greatly reduces the size of the matched file relative

[21] All of our programs used to clean and merge the data are available. We are not, however, able to share the data. The CompStak data is proprietary and can be obtained through contract similar to the one we obtained from CompStak Inc. at https://compstak.com/. As for the Dun & Bradstreet data, which were obtained from the Syracuse University site license, other institutions (e.g. other universities, the New York Public library) have similar licenses.

to the D&B sample. Additional observations are lost because we are not able to reliably link records, either because of missing information (e.g., street address) or different spellings of street names and/or tenant names beyond what would allow for a reliable match. All together, these limitations reduce our initial matched file to 183,318 records.

To reduce the effect of outliers, we dropped records with leases shorter than 6 months and those longer than 30 years. Deleting observations with missing controls reduces the sample size further, with missing values for establishment age (from D&B) being most limiting. Moreover, to ensure a consistent sample across specifications, most regressions are estimated using a common set of observations for which all controls used across the various models are present. Nevertheless, despite these adjustments, the resulting sample is still very large, with 127,872 matched records.

Panel A of Table 1 provides the sample shares for the urban areas mentioned above. Restricting the sample to the final cleaned set of observations used in our estimation, California cities make up roughly 61% of our sample, New York City and northern New Jersey together account for another roughly 17.5%, and the rest of the leases are spread across the other locations noted above.

A more subtle feature of the matched sample concerns the temporal coverage of leases and companies. Because of the nature of the CompStak sharing arrangement with commercial agents, leases drawn from CompStak records include contracts executed going back many years, in some instances to the 1980s. This pattern is evident in Panel B of Table 1, which shows that roughly 4.5% of leases were executed prior to 2000. Most, however, were executed in more recent years, including roughly 32.1% between 2010 and 2014, 34.5% between 2015 and 2019, and 3.3% in 2020 and 2021.

The D&B data has different temporal features. It is a cross-section of companies present at a given point in time. As such, the 2018 D&B data do not include companies created after 2018 (allowing for reporting errors). For that reason, any leases in the matched file that were executed in 2020 and 2021 are renewals of existing leases for companies that were present in 2018 in the D&B database (filters in our programming ensure this is the case).

More important, the D&B data file is designed by Dun & Bradstreet to be valuable to companies seeking information on present-day potential clients and business partners. For that reason, D&B drops failed companies (with a lag). This pattern is worth noting because across the United States, on average roughly 50% of newly created businesses fail in their first five years and nearly 70% fail in their first ten years.[22] For these reasons, our matched sample, which is comprised of establishments present in 2018 that initiated leases in 2018 or earlier years, is skewed towards older companies that have survived their first years in business. For that same reason, for most observations in the matched sample, the age of the company when observed in 2018 is older than when its lease was executed. This pattern is evident in Table 1, which reports summary measures for the lease and establishment attributes in our estimating sample. In Panel D, median and mean establishment age in 2018 are 12 years and roughly 18.4 years, respectively. By comparison, for these same establishments, median and mean age when their lease contracts were executed – calculated as 2018 minus the year in which CompStak reports the lease as having been originated – are 6 and 12.8 years, respectively.[23]

3.2. Dependent variables

In our lease-length regressions, the dependent variable is the log of lease length in months, denoted **Log(Lease length)**. In the regressions exploring the term structure of rental contracts, we use the log of effective monthly rent per square foot as the dependent variable, denoted **Log(Lease rate/sqft)**. Effective rent is a standard industry measure and is calculated by CompStak as gross rent less the amortized value of concessions and incentives, with free months of rent up front being one example. Note that information on rent escalator clauses is only available for about half the observations and is not used in the estimation for that reason.[24]

3.3. Locational controls

Recent work by Liu, Rosenthal and Strange (2018) and Rosenthal, Strange and Urrego (2022) shows that nearby employment density has a sharp, positive effect on commercial lease rates, reflecting longstanding arguments in the agglomeration literature that density enhances worker productivity, increasing rent premia in business centers (see Behrens and Robert-Nicoud (2015), Combes and Gobillon (2015), Duranton and Puga (2004), and Rosenthal and Strange

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[22] Establishment survival rate is reported by the U.S. Bureau of Labor Statistics at https://www.bls.gov/bdm/us_age_naics_00_table7.txt. For a discussion of the high failure rate among startup companies see https://www.smallbusinessfunding.com/small-business-success-and-failure-rates/. Insufficient cash flow because of slow-paying customers is one of the reasons highlighted for business failure, consistent with the Dun & Bradstreet risk assessment measure described shortly.

[23] Because of reporting errors, in about 25% of records the adjustment results in a negative adjusted age. In such instances, we set the adjusted age to 1.

[24] The median observed escalator rate among these observations is 3% per year.

(2004, 2020) for reviews of the agglomeration literature). Other fundamental location-specific features of a business location include available supply of commercial office space, local regulations and possible restrictions on rent, proximity to attractive amenities (e.g., a scenic park), and more. Together, these and related local attributes affect the intensity of competition for space in a building and are first-order drivers of commercial rent.

To allow for location effects, in our more simply specified models we control for the log of employment density (employment per square mile) for the zip code containing the leased space, denoted **Log(Emp/sqmi zipcode)**. As will also become apparent, in many instances lease observations are concentrated in the same city, zip code, and even in the same building. This pattern allows us to make use of city, zip code and building fixed effects in our more fully specified regressions. In some models we control for 1,045 city fixed effects. In other instances, we include 1,868 5-digit zip-code fixed effects, and in our most rigorous specifications, we draw on 38,031 individual building fixed effects.

City fixed effects encompass broad features of an urban area that affect commercial rent. However, those features are not refined enough to capture neighborhood-specific attributes of a business environment that affect an entrepreneur's choice of location within a city (see Rosenthal and Strange (2020) for a recent discussion of related literature). Zip-code fixed effects go further and capture extensive information about a rental suite's immediate neighborhood. But even then, such controls do not allow for building-specific attributes that draw potential tenants to specific buildings. Such attributes include the physical and management features of a building and/or the presence of valued business partners elsewhere in the building. Liu, Rosenthal and Strange (2024), for example, demonstrate that in commercial office buildings, the presence of an anchor tenant attracts other smaller companies to the building that operate in the same industry as the anchor (including retail, finance, law, advertising, and software development), echoing previously established patterns in retail shopping malls as documented by Brueckner (1993), Pashigian and Gould (1998) and others.[25] Our ability to control for building fixed effects allows us to address these and related considerations that could otherwise confound estimates of the rent-risk

[25] Liu, Rosenthal and Strange (2021) also show that commercial companies may even care more about the type of tenants on their own floor as compared to tenants just three floors away, about the distance beyond which most business workers are likely to use an elevator.

relationship. In addition to locational fixed effects, our regressions include a fixed effect for the year that the lease was executed.

3.4. Establishment risk and age

The primary risk measure on which we based our empirical analysis is a discrete firm-level measure created and marketed by D&B. For each firm, D&B computes a "failure score" designed to reflect the likelihood that a firm will be unable to pay its bills in the next 12 months. The score is based on a company's age, its type (corporate vs. non-corporate), active lawsuits, liens or judgements, company net worth, and trade data, which captures the number and dollar amount of "payment experiences" involving the company along with the share that were "satisfactory."[26] The algorithm used to compute the failure score is not reported by D&B but likely entails a nonlinear combination of the terms just noted. D&B then codes the score into four 1-0 discrete categories and, in the data we had access to, reports only those measures. These include, low, medium and high risk, captured by the dummy variables **Risk_Low**, **Risk_Med** and **Risk_High**, respectively, in addition to **Risk_NA** for instances where D&B does not have sufficient information to compute a failure score. Absence of information about the riskiness of a tenant seems likely to cause landlords to treat such tenants as risky relative to those with a favorable risk classification. Evidence presented later supports that interpretation.

In the regressions that follow we also condition on log of establishment age at the time the lease was originated, **Log(Age estab)**. We do so because age may affect lease length and the rental rate through other channels beyond its influence through the D&B risk measure. In the case of lease length, for example, established firms may be confident of their future space needs and may thus prefer to sign longer-term leases to avoid future relocation costs. In the case of the lease rate, established companies may be more able to secure suites with especially valuable features based on productivity advantages and/or amenities such as proximity to valued business partners, transportation hubs, scenic parks, and more.[27]

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[26] Additional details are available the D&B website: https://www.dnb.com/resources/financial-stress-score-definition-information.html.

[27] Our extensive set of controls, including the age measure, should limit the possibility of bias in the risk coefficients due to omitted variables that are correlated with the risk measures. However, a referee suggested a different source of potential bias due to reverse causation. The argument is that longer lease contracts may lead tenants to invest in utilizing the space more effectively, with the resulting improvement in operational conditions reducing riskiness and the chance of default. While we cannot gauge the importance of this channel, such behavior could occur.

Because established companies are known to be less risky than newly created establishments (given the high failure rates of new firms), in the regressions that follow we explore the effect of age on the coefficients of the risk measures. In some instances, we do so by running models with and without the age control. In other instances, we estimate a series of age-stratified regressions from one-year old companies up to those over 10 years in age. For newly created companies, age does not contribute to variation in the D&B risk measure, which instead depends entirely on its other components as described above. For very established companies, perceived risk associated with the tenant will tend to be quite low, with the firm having survived beyond their first decade. For this group, evidence of a systematic age-related effect is suggestive of effects arising for reasons other than concerns about lease default risk.

3.5. New tenant arrival versus renewal leases

Another instance in which a landlord's awareness of how risky a tenant may be arises when comparing leases offered to new arrivals to a building (**New**) as compared to renewals on leases for existing tenants (**Renewal**). Landlords have less information on newly arrived tenants, and for that reason, we anticipate that they will place more weight on the D&B risk measure than for renewal tenants. For the latter, landlords have personal knowledge of the tenant's rent payment history. We test for these patterns using two sets of models. In the first, all of the tenant attributes including the risk measures and others described just below are interacted with New versus Renewal lease status. This specification restricts the lease-year and location fixed effects to be alike for the two types of leases. In our second set of models, the lease-year and location fixed effects are also interacted with the New versus Renewal status of each lease making this a fully-interacted model, equivalent to a sample-stratified regression. In both cases, zip-code and building fixed effects regressions are estimated. Results from the two sets of models allow us to check for robustness including differences in the risk coefficients for New and Renewal leases.[28]

[28] It is worth noting that new tenants are of two types. They include newly created companies and existing companies that are relocating to a new building. In our estimating sample, the latter group accounts for roughly 53% of new tenants. The rich set of controls in the interaction models described above do much to address differences between these two groups of establishments and especially so given the extensive location fixed effects included in the models.

3.6. Additional establishment and lease controls

Additional controls used in most regressions include dummy variables indicating the 1-digit SIC code of the tenant. Some industries, such as retail, rely on a regular flow of patrons to their establishment site. In such instances, having a stable long-term location will help to retain repeat customers and, for that and related reasons, we anticipate that retail lease length will be longer than for other tenant types. Such mechanisms seem less relevant, for example, in the case of manufacturing, where customers only rarely visit the site.

Among the features of the lease, we control for when the contract was signed by including fixed effects for the year of execution of the lease. Other lease attributes include the amount of space leased, denoted as **Log(Space leased sqft)**. Tenants seeking more space are likely to have higher relocation costs, which could prompt them to favor longer leases. Working in the opposite direction, we also control for establishment employment per square foot of space leased, **Log(Wrkrs/sqft leased)**, which captures crowding in the workspace. A high value could indicate long-term inadequacy of the amount of space leased and hence a desire for a short-term contract. To compute this variable, we divide the 2018 level of employment reported by D&B by space leased from CompStak. Although we recognize that thriving businesses will grow, we have no way to reliably measure establishment employment at the time the lease was executed.

Liu, Rosenthal and Strange (2018) demonstrate that commercial rent varies vertically in tall buildings in a systematic fashion. In sufficiently tall buildings, rent is high at ground level, reflecting the value of street access. Rent then falls sharply just above ground level and rises thereafter with height and related view amenities. Accounting for these effects, in the rent regressions we control for a suite's height off the ground allowing for the non-linear pattern just described.

3.7. Summary statistics

Panel C of Table 1 provides summary statistics for the D&B risk measures described above. Reading left to right across the five columns, the panel reports mean values for the full sample and samples stratified by age of establishment from less than or equal to 1 year in age to over 10 years in age. Overall (column 1), 60% of tenants are in the low-risk category, with roughly 9% falling into both the medium and high-risk categories, and 21.6% in the Risk_NA group for which D&B does not have sufficient information to provide a risk assessment. Importantly, and as might be expected, the frequency of low-risk ratings increases sharply with establishment age while the frequency of missing risk assessments declines. For age-1 establishments (column 2), the corresponding samples shares are 40.7% and 36.5%, while for companies older than 10 years (column 5), the corresponding samples shares are 76.9% and 10.0%.

Turning to Panel D, average lease length is 5-1/2 years (66.6 months) while average effective rent per square foot is a $37.83 (in 2018 dollars). Newly arrived tenants in a building comprise 57% of the lease observations, with the remaining 43% of leases being renewals for existing tenants. As noted above, average establishment age in 2018 – the year the D&B data are observed – is older than the year in which a company's observed lease contract is executed. These values average 18.4 years and 12.8 years, respectively, with corresponding median values (column 5) of 12 and 6 years. Leased space averages roughly 22,310 square feet, with the average and median number of workers per square foot equal to 4.4 and 1.5 workers per 1,000 square feet, respectively. Headquarters account for 16.2% of observations and zip-code employment per square mile averages 96,561 with a median value of 7,510.

In Panel E, roughly 52% of leases are for service sector firms, with FIRE and Retail having the next largest shares at 13.9% and 10.3%, respectively. This pattern is characteristic of office buildings in densely developed cities, which is where the bulk of the lease observations are based.

4. Lease-length regressions

4.1. Basic results

Table 2 shows the basic lease-length regression results. The regression in column (1) contains only the risk dummies, the control for space leased (**Log(Space leased sqft)**), and fixed effects for the year the lease was executed. The age variable is initially omitted because of a potential overlap with the risk measures, and locational fixed effects are omitted as well. Lease length increases with the amount of space leased, with a highly significant elasticity of 0.19 (the t-ratio is 32). That tenants who occupy substantial floor space receive long leases seems natural, given the high costs of relocation for large tenants.

Turning to the risk dummies, the coefficients of both **Risk_Low** and **Risk_Med** are significant and positive. With high-risk as the omitted category, this pattern indicates that lower-risk tenants receive longer leases than high-risk tenants, confirming the main hypothesis. The leases of the low-risk and medium-risk tenants are, respectively, 4.98% and 4.16% longer than those of the riskiest tenants. A missing risk measure is associated with notably shorter leases relative even to the **Risk_High** omitted category. The coefficient on **Risk_NA** is -7.16% and is highly significant, consistent with the view that when landlords have little information on tenant risk, they treat the tenant as being risky. Note finally that, while the explanatory power of the regression is modest, the R^2 value of 0.17 nevertheless indicates that the simple set of controls in column (1) has predictive power.

Column (2) of the table adds **Log(Age estab)** to the regression of column 1, recognizing that age affects a firm's riskiness as well as its ability to foresee future space needs. Lease length rises with establishment age, consistent with both these channels. Importantly, the inclusion of age has only small effects on the coefficients of the risk measures and their statistical significance, with the **Risk_Low** effect coefficient falling slightly from 4.98% to 4.35%, the **Risk_Med** effect rising from 4.16% to 5.69%, and the **Risk_NA** coefficient shrinking from -7.16% to -6.00%. The similarity of the risk coefficient estimates between columns (1) and (2) confirms that the other types of information used by D&B in its risk assessment are important and that they generate notable effects on lease length when age is held fixed. This outcome shows the importance of other factors beyond age in creating variability in the D&B risk measures.[29]

Additional control variables are added in column (3), and the result is a modest decline in the **Risk_Low** and **Risk_Med** coefficients. The worker crowding variable **Log(Wrkrs/sqft leased)** has a small and insignificant effect on lease length, contrary to expectations, but that pattern reverses in later more fully specified regressions. **Headquarters** also has a significantly positive coefficient, matching expectations.

Turning to the industry coefficients, the results show that, relative to the manufacturing sector (the omitted category), tenants in industries for which there is frequent in-person interaction with visitors to an office (e.g., clients and customers) have notably longer leases. This pattern is especially strong for **Retail**, with lease lengths 44% longer, but is also present for **FIRE** and **Service**, for which lease lengths are roughly 28% and 24% longer, respectively. In all three industries, the lease length premium is also highly significant. By contrast, lease length is more similar to manufacturing in several of the other industries seen in the table.

[29] To facilitate comparison to the other model specifications in Table 1, we restricted the sample in columns (1) and (2) to be the same as for the other columns (containing 127,872 observations). Columns (1) and (2) were also estimated using a larger sample for which missing values for control measures used in later columns were not relevant. Results were very similar to those described above.

Column (4) adds zip-code employment density, **Log(Emp/sqmi zipcode)**, which has a positive effect on lease length: the lease-length elasticity is 5.7%, consistent with tenants valuing densely developed locations with potential to yield benefits from other nearby economic activity. The presence of employment density reduces the effect of many of the other variables whose coefficients are often somewhat smaller in magnitude as are the associated t-ratios, but not enough to change to qualitative patterns noted above. The primary exception is for **Headquarters** for which the coefficient shrinks by about half and the t-ratio declines from 3.1 to 1.6. For the measures of primary interest, the magnitude of the **Risk_Med** coefficient also shrinks by almost half and is now only marginally significant, but the **Risk_Low** coefficient remains close to its value in column 3 with a t-ratio of 3.8, and the coefficient on **Risk_NA** becomes somewhat larger.

The remaining columns of Table 2 show the effects of adding city, zip-code and building fixed effects to the lease-length regression. When city fixed effects are added in column (5), the **Risk_Low** coefficient declines from roughly 3.4% to roughly 3.0% but remains significant, while many other coefficients become even smaller in absolute value, reinforcing their previous changes. The effect of zip-code employment density largely disappears, with a near zero coefficient.

Column (6) replaces the city fixed effects and zip-code employment density with 1,868 zip-code fixed effects. Results are mostly similar to those in column (5), although the negative **Log(Wrkrs/sqft leased)** coefficient becomes larger and is now significant, as was originally anticipated. Column (7) includes 38,031 individual building fixed effects, the most granular geographic control. The **Risk_Low** coefficient is nearly identical in size to its values in the city and zip-code fixed effects models and has a t-ratio of 3.32. In contrast to the results in columns 1-4, which showed a 3.41-4.98% longer lease length for low-risk tenants, columns 5-7 indicate that the leases of these tenants are closer to 3% longer than those of high-risk tenants.

The coefficient on establishment age is very precisely estimated in all of the models in Table 2 but with a notably larger elasticity upon controlling for building fixed effects in column 7; in that model the elasticity is 3.24% with a t-ratio of almost 15. The building fixed effects control for choice of building with all of its associated attributes. Having also conditioned on the D&B risk measures, the large age elasticity in column (7) is suggestive that more established companies may be better able to anticipate future space needs and seek longer leases to reduce future relocation costs. We provide further evidence on this point in a later table.

Mirroring the pattern for age of tenant, the coefficient on **Log(Wrkrs/sqft leased)** in column (7) becomes notably more negative than in the earlier columns and highly significant with a t-ratio of nearly 6.0. Here too the presence of building fixed effects allows the anticipated pattern to emerge, in this case in support of the conjecture that establishments signing leases for crowded space choose shorter contracts.

As might be expected, adding in more refined location fixed effects reduces the magnitude of the coefficients for the Retail, FIRE and Service SIC codes. However, even with building fixed effects, the core patterns for these controls remains robust and the coefficients remain significant. This pattern reinforces the view that establishments that rely on in-person interactions favor longer leases.

4.2. Stratification by age

To gain a fuller sense of the interaction between an establishment's age and the risk measures in determining lease length, Table 3 presents regressions stratified by age categories: establishments 1 year old, 2-5 years old, 6-10 years old, and older than 10 years. Within the second and third age ranges, the establishment's age level is captured by fixed effects (reported at the bottom of the table), and in the last, unbounded category, age is captured by the continuous variable used before. Note that apart from stratifying by age, the model specifications in columns 1-4 and 5-8 mirror the models presented in columns (2) and (6) of Table 2, respectively: the first group contains controls only for risk, age, space leased, and lease-year fixed effects, while the second group adds in the other covariates along with zip-code fixed effects.

Most of the core qualitative patterns in Table 3 are the same as in Table 2. The primary and notable difference is for established companies beyond 10 years in age. First, however, we discuss patterns for the younger establishments (10 years or less in age). Among such companies, and for both the restricted and more fully specified models (columns 1-3 and 5-7, respectively), the **Risk_Low** coefficient is always positive and significant (or nearly so), as in columns (2) and (6) of Table 2. Also as in Table 2, the coefficient on **Risk_Med** is positive and significant in the restricted model in columns 1-3, but smaller in magnitude and not significant when additional controls are added to the model. The elasticity of lease length with respect to space leased is in the 17-19% range across the columns in Table 3, close to estimates in Table 2.

The pattern for older establishments in columns (4) and (8) of Table 3 is different. For this group, and for both the restricted and more fully specified models, the **Risk_Low** and **Risk_Med** measures both have small and insignificant effects on lease length. This outcome seems likely to arise because seasoned, successful companies often have track records that can be readily verified by a landlord, making the D&B risk assessment measure less relevant. In contrast and focusing on the more fully specified models, the **Risk_NA** coefficient in column (8) is negative, highly significant, and large (6.9%), as it is for the younger age groups in columns 5-7. This pattern echoes estimates from Table 2 and suggests again that if D&B is unable to assess a prospective tenant's risk, landlords are likely to view such companies as risky.[30]

Also notable in Table 3, the estimated age elasticity for older establishments over 10 years in age in columns (4) and (8) is large, positive and highly significant, with values of 9.8% and 5.5%, respectively. While age partly proxies for risk, the small and insignificant coefficients on **Risk_Low** and **Risk_Med** in columns (4) and (8) suggests that something other than risk is driving the age effect for older companies. As suggested earlier, a likely mechanism is that, as companies become ever more established, their future space needs become more stable, increasing tenant preference for a longer lease.

4.3. Renewal vs. new tenants

Comparing lease renewals to leases extended to new tenants provides a different opportunity to demonstrate that landlords take risk into account when writing lease contracts. Because landlords do not have a prior history with a new tenant, we expect new tenants to be viewed as riskier than existing tenants who are renewing a lease. Tables 4a and 4b present estimates from lease-length models that allow for this and other possible differences between new and renewal lease observations using the same fully specified models as in columns (6) and (7) of Table 2 (with zip-code and building fixed effects, respectively). Table 4a reports models in which the **New** versus **Renewal** status of a lease is interacted with the risk measures and other tenant attributes while restricting the lease-year and location fixed effects to be alike for the two types of

[30] For the restricted models in Table 3 (columns 1-4), a strong negative coefficient on **Risk_NA** is present for newly created establishments (age = 1) in column 1 while estimates for the other age groups are small, not significant and sometimes positive. We emphasize estimates from the more fully specified models in the text because we view estimates from those models as more reliable.

leases. Table 4b reports estimates from fully interacted models that add in interactions for the lease-year and location fixed effects, equivalent to running sample-stratified regressions.

For both Tables 4a and 4b, estimates from each regression are spread across three columns to facilitate comparison of coefficients between the two lease types. In each case, interaction terms are formed by multiplying the slope controls (measures other than the fixed effects) by the new-tenant lease dummy (**NewL**) for new-tenant observations and by a renewal-lease dummy (**1-NewL**) for existing tenant lease renewals. Coefficient estimates for New and Renewal lease observations are then reported in columns (1) and (2) for the zip-code model and (5) and (6) for the building fixed effect model. The adjacent columns, (3) and (6), respectively, report the difference in estimates for the two lease types along with their associated t-ratios. These estimates were obtained by rerunning the regressions with the **1-NewL** interaction set equal to 1 for all observations so that coefficients on the NewL interaction terms capture differences for the two lease types. Lastly, in Table 4b, analogous adjustments were made to create interactions for the lease year and location fixed effects.[31]

Results from Tables 4a and 4b echo patterns from the age-stratified regressions described above. We begin with the partially interacted zip-code fixed effect model in columns 1-3 of Table 4a. For new arrival tenants (column 1) the coefficient on **Risk_Low** is once again large, positive and significant, with a 4.26% increase in lease length relative to high-risk tenants. The coefficient on **Risk_Med** is smaller, 1.98% with a t-ratio of 1.56, but also clearly positive. These coefficients differ sharply from those for renewal leases in column (2), which are smaller in magnitude and insignificant (and of the wrong sign for Risk_Med). Observe also that the differences in the low

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[31] For each model in Tables 4a and 4b, two regressions were run to generate the estimates spread across the corresponding three columns. These were of the following form,

(i) $\text{Log(lease length)} = b_1 * \mathbf{NewL} * X + b_2 * (\mathbf{1\text{-}NewL}) * X + \text{LeaseYear}_{\text{FixedEffects}} + \text{Location}_{\text{FixedEffects}}$

(ii) $\text{Log(lease length)} = c * \mathbf{NewL} * X + b_2 * X + \text{Lease-Year}_{\text{FixedEffects}} + \text{Location}_{\text{FixedEffects}}$

where X are controls and the location fixed effects are at the zip-code or building level depending on specification. The coefficients b_1 and b_2 capture effects for new-arrival and renewal leases, respectively, and are reported in the first two columns for each model. The coefficient c from the second regression measures the difference in estimates for the two lease types ($c = b_1 - b_2$) and is reported along with its t-ratios in the third column for each model. In Table 4a, lease-year and location fixed effects are entered as in the earlier tables. In Table 4b, the lease-year and location fixed effects were interacted with the New/Renewal status of the lease record. This interaction was achieved by first coding separate unique lease year and location values for the new arrival and renewal leases (e.g. 2010 and 1010 for new arrival and renewal leases executed in 2010, respectively). Lease-year and location fixed effects were then included in the models using the same estimation routines as in the other tables.

and medium risk coefficients between the two lease types as reported in column (3) are both roughly 3 percentage points with t-ratios of 2.14 and 1.60, respectively. Overall, these patterns suggest that the D&B risk measures have little role in determining lease length for existing tenant lease renewals while being more informative for landlords when considering a new tenant.

Additional patterns in columns 1-3 of Table 4a reinforce other results from the age-stratified models in Table 3. Regardless of **New** versus **Renewal** status, an establishment without a D&B risk assessment appears to be treated as high-risk, with strong, negative and significant coefficients on **Risk_NA**. Also, establishment age has a large and significantly positive effect on lease length regardless of tenant type. For existing tenant lease renewals, this pattern further supports the idea that seasoned companies have more clearly defined future space needs and may sign longer leases in part for that reason.

The building fixed effect model in Table 4a and the fully-interacted models in Table 4b allow us to check for robustness. Replacing zip-code fixed effects in Table 4a (columns 1-3) with building fixed effects (columns 4-6) does not change the patterns above although t-ratios tend to be lower as might be expected given the large increase in fixed effects. The same is true when shifting to the fully interacted models in Table 4b. Despite including separate lease-year and location fixed effects for new and renewal lease observations, the **Risk_Low** coefficients remain large, positive and significant for new arrival leases but smaller for renewals. The difference in elasticity is substantial (2.7 percentage points) in the zip-code model and marginally significant (the t-ratio is 1.78) but smaller and not significant in the more heavily parameterized building fixed effect model. The coefficients on **Risk_NA** continue to be large, negative and highly significant in both the zip-code and building fixed effect models while the coefficients on age are also always positive, large and highly significant.[32]

Overall, the mix of estimates in Tables 4a and 4b reinforce key patterns from the age-stratified models in Table 3. Results suggest that for tenants for whom landlords have limited information, landlords are more willing to issue longer leases when the tenant has a D&B low-risk

[32] The models in Table 4a also include a new arrival 1-0 dummy variable (**NewL**). The coefficients on that measure are 14.3% and 12.6% for the zip-code and building fixed effect models, with t-ratios of roughly 5 in both cases. Because these models restrict the lease-year and location fixed effects to be alike for new arrival and renewal leases, the **NewL** estimates suggest that new arrival leases were executed at a time and location where longer leases were more common. Any such tendency is subsumed by the fixed effects in Table 4b where separate lease-year and location fixed effects are included for new and renewal observations (causing the **NewL** control to drop out of the models).

assessment. This differs from established companies for whom a low-risk D&B rating has little effect on lease length in most model specifications. Also, among existing tenants seeking lease renewals, evidence is suggestive that greater awareness of future space needs may be contributing to tenant preferences for longer leases.

4.4. Restricting sample to the largest cities

Table 5 provides a robustness check by including only leases for the three largest cities, New York, Chicago, and Los Angeles. Estimates are provided that distinguish between young (ages 1 through 5 years) and old (age above 10 years) tenants – columns (1) and (2) – and between new tenants and renewal tenants – columns (3) and (4) – while using zip-code fixed effects. The sample sizes are reduced by about half for each group under this big-city restriction.

Once again, the core patterns are robust. Estimates in Table 5 show exactly the same risk-coefficient patterns as in Table 3 for the age-stratified models and as in Table 4a for zip-code fixed effect models stratified by new arrival and renewal lease status. For both sample decompositions, the **Risk_Low** coefficient is positive, large and significant for less well-known tenants – those who are young or newly arrived to a building – while much smaller and not significant for tenants with a track record – older tenants or existing tenants. For all sample groups, **Risk_NA** once again has a large, negative and significant coefficient. Also for all groups, establishment age has a large, positive and highly significant effect on lease length for older companies (column 2) and renewals for existing tenants (column 4).[33] Overall, Table 5 reinforces the previous findings on risk effects.

5. Term-structure regressions

The discussion now turns to a different potential impact of tenant riskiness in the market for commercial space: the effect of riskiness on the term structure of leases. As explained earlier, long-term leases tend to have higher rent levels than short-term leases, and the question is whether this premium is larger for risky tenants, some of whom will select long-term leases even though the previous analysis shows that their lease lengths tend to be shorter on average.

Although the model of section 2 does not explore the effect of tenant riskiness on the lease term structure, Ambrose and Yildirim (2008) and Agrawal et al. (2011) carry out this exercise

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[33] The effects of the other controls in the model are also similar to those in Tables 3 and 4. As an example, the **Retail** coefficient is large, positive and highly significant for all sample groups.

using option-based models and numerical simulation. Their results predict a steeper term structure for risky than for low-risk tenants, confirming the intuition presented in the introduction. We use our data to test this prediction, supplementing the simulations carried out by Ambrose and Yildirim (2008) and Ambrose et al. (2011) and providing evidence in support of the results from these two previous papers.[34]

We estimate the term-structure/risk relationship in a series of lease-rate regressions presented in Table 6. In all cases, the dependent variable is **Log(Lease rate/sqft)**, the log of effective (initial) rent per square foot. In addition to term structure, the model specifications control for other core determinants of commercial rent. Following Liu et al (2018), these include (i) the scale and composition of nearby business activity, drivers of local agglomeration economies that enhance productivity; (ii) other local attributes that enhance productivity, such as proximity to public transit or a port facility; (iii) suite floor number, which proxies for the combined effects of ease of street access (which decreases with height) and height-related amenities (which increase with height); and finally, (iv) physical features of the building that may enhance both workplace amenities (e.g., marble floors) and productivity (e.g., elevator speed). In the models that follow, some of these drivers like floor number are included directly in the regressions. In other instances, we use zipcode and building fixed effects to capture the effects of neighborhood and building-specific attributes.

Because suite floor number is missing for many lease records, sample size in the lease-rate regressions is smaller than for the lease-length models. The lease rate is also likely especially sensitive to neighborhood and building-specific attributes, leading us to place greater emphasis on the building fixed-effect models that follow. For both reasons, the power to identify key patterns is reduced. To offset that effect, and to simplify discussion below, we collapse the tenant risk categories to two, low and medium-high, with the first identified by the previous **Risk_Low** dummy and the second containing both medium- and high-risk tenants based on the **Risk_Med** and **Risk_High** dummies. This second group is referred to as risky in the discussion below.

In Table 6, columns 1-3 report regressions based on samples that include both low- and high-risk tenants. The primary controls of interest are **Log(Lease length)**, the **Risk_Low** dummy

[34] Ambrose et al. (2011) use the Dun & Bradstreet risk score as a covariate in a regression that relates the lease rate to the lease term. However, since this specification does not allow the lease-term coefficient to differ by the risk level of the tenant (which would require an interaction term), it does not provide a test of the theoretical connection between risk and the term structure, in contrast with our results. The regression, however, tests other predictions of their model.

variable, and the interaction between these two measures, which is written as **Risk_Low* Log(LL)** in the table. Specified in this way, the coefficient on **Log(Lease length)** captures the term-structure slope for risky tenants, which is expected to be positive. That coefficient plus the coefficient on the interaction term measures the term-structure slope for low-risk tenants, while the t-ratio on the interaction term tests whether the two slopes differ. If tenant riskiness increases the slope of the term structure, as hypothesized, the interaction coefficient should be negative, implying a flatter slope for safer tenants.

Column (1) includes log of zip-code employment density along with the risk measures, lease-length, and lease-year fixed effects and is estimated using the largest sample possible, with 139,757 observations. Column (2) repeats this regression restricting the sample to just those observations available for the more fully specified models reported elsewhere in the table, 62,571 observations. Importantly, results from the two models are similar, indicating that the difference in samples does not appear to affect the core patterns.

Consistent with Liu et al (2018), lease rate increases significantly with zip-code employment density, with elasticities of 13.9% and 16.3% in columns (1) and (2), respectively. The **Risk_Low** coefficients are both positive and significant, with coefficients of 25.7% and 39.2%, consistent with expectations that lower-risk tenants occupy higher quality suites. The elasticity of the lease rate with respect to lease length is roughly 20% and highly significant in both regressions; this estimate, which pertains to risky tenants, indicates an upward-sloping pattern. Most important, the interaction terms are negative and also significant, with coefficients of 6.5% and 10% in columns (1) and (2). These estimates confirm the prediction of Ambrose and Yildirim (2008) and Agrawal et al. (2011) that the rental term structure is flatter for low-risk tenants, thus being steeper for risky tenants.

Column (3) adds additional controls to address possible unobserved factors. Zip-code employment density is replaced with over 1,500 zip-code fixed effects that capture a wide range of neighborhood attributes. Other controls include establishment age, space leased, crowding, and controls that capture the quality of space ("suite" attributes). These latter measures include **Ground level**, a dummy variable indicating that the space is on the second or lower floor of the building, and **Log (Floor Num)**, equal to the log of the floor number plus 1. This specification allows rent to change continuously with the floor number while being discretely different for floors below 2 (which include basement space), as in Liu et al. (2018).

The added controls in column (3) perform as anticipated. Rents fall with establishment age, fall with the amount of leased space, and rise with the floor level above floor 1. Rent is higher for headquarter tenants, and higher than manufacturing rent (the omitted SIC code) for mining, retail, FIRE, service and government tenants. Construction and wholesaler tenants pay lower rent. Most important, the risk and lease length terms again support the main hypothesis, with their interaction indicating that the slope of the lease-length term structure is 5% lower for low-risk tenants.

Columns (4) and (5) repeat the zip-code fixed-effects model in column (3) while stratifying the sample into low-risk (column 4) and risky (column 5) observations. This division greatly expands the set of controls by allowing for fully separate zip-code fixed effects in addition to different estimates for the other model controls. Despite the expanded specification, the patterns are nearly the same as before, including the point estimates of the low- and high-risk term structure coefficients. In column (3), those estimates are 0.191 for high-risk tenants – the coefficient on log of lease length – and 0.142 for low-risk allowing for the interaction term (with 0.142 = 0.191 – 0.049). In columns (4) and (5), the corresponding estimates in the sample-stratified models are 0.192 and 0.139, respectively.

Columns 6-8 repeat the models in the previous three columns but replace the zip-code fixed effects with building fixed effects. These fixed effects control for a host of building-specific attributes including physical features of the building and attributes of its immediate and broader location. Adding the building fixed effects reduces the magnitude of the estimated term structure coefficients but does not change the core pattern. In column (6), the interaction term indicates that the elasticity of rent with respect to lease length is roughly 2.4 percentage points lower for low-risk tenants. In columns (7) and (8), the lease-length elasticities for risky and low-risk tenants are 7.9% and 6.8%, respectively. Once again, term structure is flatter for low-risk tenants.

6. Conclusion

This paper has explored the connection between tenant riskiness and both commercial lease length and the term structure of rents, linkages that have not been investigated in the prior empirical literature. Our theoretical model highlights the possibility of default on a long-term lease as a driver of the risk/lease-length connection. The empirical results have shown that, among new tenants, those with lower risk get longer leases, as predicted. But among existing tenants who are renewing a lease, riskiness as measured by the Dun & Bradstreet index has no effect on lease length. Evidently, for a landlord whose experience with an existing tenant has been favorable enough for a lease to be renewed, an outside appraisal of riskiness like that of D&B carries little additional weight. A greater age for the establishment, however, serves in part as a risk proxy for both new and existing tenants, with older establishments getting longer leases. Evidence also suggests that age may also make a firm's future more predictable, leading to longer leases.

Beyond its demonstration of a link between tenant riskiness and lease length, the paper offers further insight into the economics of leasing by showing that the term structure of lease contracts is connected to the riskiness of tenants. Our results confirm that lease rates are higher on longer term leases, a common explanation for which is to compensate lenders for inflation risk. Since bad tenant behavior (such as making late payments or default) also has a greater chance of occurring over a longer contract, that too should prompt landlords to require a higher rent premium when renting long-term to a risky tenant. Our results provide support for this tendency as well, suggesting that lease term structures estimated in previous work, which did not control for tenant riskiness, were a blend of this high premium and the lower one associated with low-risk tenants.

Table 1: Summary Statistics [a]

Panel A: Lease Location	Frequency	Percent	Cum. %
Boston MSA	9,106	7.12	7.12
California Major Cities	78,043	61.03	68.15
Chicago	9,276	7.25	75.41
Washington DC	5,701	4.46	79.87
Northern New Jersey	3,882	3.04	82.90
New York City	18,547	14.50	97.41
Philadelphia	3,317	2.59	100
TOTAL	127,872	100	

Panel B: Year Lease Executed	Frequency	Percent	Cum. %
Pre-2000	5,689	4.44	4.44
2000 to 2004	11,654	9.12	13.56
2005 to 2009	21,092	16.50	30.06
2010 to 2014	41,109	32.14	62.20
2015 to 2019	44,142	34.52	96.72
2020 to 2021	4,186	3.27	100
TOTAL	127,872	100	

	Full Sample	Age <= 1	Age 2 to 4	Age 6 to 10	Age 10+
Panel C: Risk Measures	127,872	39,429	21,616	20,090	46,737
Risk_Low	0.604	0.407	0.577	0.635	0.769
Risk_Med	0.091	0.151	0.102	0.075	0.042
Risk_High	0.089	0.077	0.102	0.100	0.089
Risk_NA	0.216	0.365	0.218	0.190	0.100

Panel D: Lease/Estab Attributes	Obs	Mean	10^{th} Pctl	50^{th} Pctl	90^{th} Pctl
Lease length (months)	127,872	66.65	24	60	120
Effective rent/sq. foot ($2018)	127,872	37.83	9.72	29.27	69.08
New tenant lease	127,872	0.57	0	1	1
Age estab in 2018 (yrs)	127,872	18.42	3	12	39
Age estab at lease execution (yrs)	127,872	12.85	0	6	33
Leased space (1,000 square feet)	127,872	22.31	1.20	5.04	42.50
Workers/sqft in leased space (1,000 sqft)	127,872	4.44	0.15	1.51	7.04
Headquarters	127,872	16.25	0	0	1
Emp/sqmi zipcode	127,872	96,561	1,155	7,510	331,005

Continued next page

Table 1 (continued): Summary Statistics [a]

Panel E: Industry	Obs	Mean	**Industry**	Obs	Mean
Not classified	127,872	0.0115	Wholesale	127,872	0.0661
Agricultural	127,872	0.0043	Retail	127,872	0.1027
Mining	127,872	0.0007	FIRE	127,872	0.1393
Construction	127,872	0.0254	Service	127,872	0.5192
Manufacturing	127,872	0.0854	Government	127,872	0.0041
Transport/Utilities	127,872	0.0412			

[a] Matched CompStak and Dun and Bradstreet establishment level sample.

Table 2: Log Lease Length – Core Estimates[a]

	(1) Risk+Space	(2) Age	(3) Estab Atrib	(4) Density	(5) City FE	(6) Zip-code FE	(7) Bldng FE
Log (Emp/sqmi zipcode)	-	-	-	0.0571	0.0001	-	-
	-	-	-	(11.55)	(0.01)	-	-
Risk_Low	0.0498	0.0435	0.0393	0.0341	0.0298	0.0288	0.0288
	(5.21)	(4.56)	(4.28)	(3.82)	(2.29)	(3.59)	(3.32)
Risk_Med	0.0416	0.0569	0.0420	0.0217	0.0105	0.0085	-0.0106
	(2.99)	(4.33)	(3.38)	(1.73)	(0.54)	(0.66)	(-0.93)
Risk_NA	-0.0716	-0.0600	-0.0654	-0.0774	-0.0831	-0.0819	-0.0864
	(-6.73)	(-5.82)	(-6.30)	(-7.62)	(-9.36)	(-8.87)	(-8.41)
Log (Age estab)	-	0.0212	0.0271	0.0199	0.0138	0.0146	0.0324
	-	(6.11)	(7.07)	(5.38)	(3.50)	(5.75)	(14.96)
Log (Leased space sqft)	0.1886	0.1861	0.1977	0.1795	0.1863	0.1925	0.1988
	(32.18)	(32.84)	(44.28)	(43.59)	(36.53)	(51.26)	(51.46)
Log (Wrkrs/sqft leased)	-	-	0.0004	-0.0037	-0.0045	-0.0057	-0.0136
	-	-	(0.12)	(-1.27)	(-1.59)	(-2.45)	(-5.98)
Headquarters	-	-	0.0286	0.0129	0.0008	-0.0010	-0.0045
	-	-	(3.10)	(1.58)	(0.09)	(-0.13)	(-0.62)
Industry NC	-	-	0.2429	0.1724	0.1090	0.0900	0.0645
	-	-	(7.06)	(5.55)	(3.34)	(3.49)	(2.65)
Agriculture	-	-	0.2757	0.2797	0.1849	0.1558	0.0337
	-	-	(6.99)	(6.85)	(5.49)	(5.21)	(0.83)
Mining	-	-	0.2427	0.1579	0.1133	0.1159	-0.0080
	-	-	(1.64)	(1.19)	(1.21)	(1.05)	(-0.10)
Construction	-	-	-0.0053	0.0041	-0.0212	-0.0193	0.0170
	-	-	(-0.29)	(0.23)	(-1.48)	(-1.34)	(0.97)
Transport & Utilities	-	-	0.0251	-0.0006	-0.0291	-0.0363	-0.0161
	-	-	(1.52)	(-0.04)	(-1.58)	(-2.22)	(-1.00)
Wholesale	-	-	0.0047	-0.0016	-0.0062	-0.0045	-0.0039
	-	-	(0.36)	(-0.13)	(-0.66)	(-0.46)	(-0.28)
Retail	-	-	0.4430	0.4125	0.3278	0.2916	0.1370
	-	-	(25.33)	(24.73)	(21.98)	(23.75)	(10.04)
FIRE	-	-	0.2790	0.1784	0.1025	0.0784	0.0229
	-	-	(14.35)	(10.20)	(3.73)	(5.98)	(1.93)
Service	-	-	0.2427	0.1737	0.1167	0.0921	0.0402
	-	-	(18.13)	(13.68)	(8.22)	(10.50)	(3.95)
Government	-	-	0.2299	0.1471	0.0502	0.0124	0.0181
	-	-	(1.76)	(1.10)	(0.33)	(0.09)	(0.24)
Observations	127,872	127,872	127,872	127,871	127,871	127,872	127,872
R-squared	0.168	0.169	0.202	0.231	-	-	-
R-squared within	-	-	-	-	0.174	0.177	0.136
Year lease executed FE	40	40	40	40	40	40	40
City FE	-	-	-	-	1,045	-	-
Zip-code FE	-	-	-	-	-	1,868	-
Building FE	-	-	-	-	-	-	38,031

[a] t-ratios in parentheses based on robust standard errors clustered at the level of the location fixed effects in columns 4-6 (city, zip code or building). Within R-square allows for location fixed effects. Year lease executed fixed effects are entered directly as 1-0 controls. Omitted industry category is manufacturing. Data are from the establishment-level matched CompStak and Dun and Bradstreet establishment level sample

Table 3: Log Lease Length – Stratified by Age of Establishment[a]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
						Age	Age	Age
		Age	Age	Age	Age = 1	2-5	6-10	> 10
	Age = 1	2-5	6-10	> 10	Zip FE	Zip FE	Zip FE	Zip FE
Risk_Low	0.0455	0.0831	0.0507	0.0096	0.0279	0.0456	0.0282	0.0055
	(2.69)	(4.70)	(2.82)	(0.60)	(1.81)	(2.82)	(1.88)	(0.41)
Risk_Med	0.0326	0.0549	0.0549	-0.0077	0.0090	-0.0096	-0.0185	-0.0244
	(1.73)	(1.93)	(1.95)	(-0.35)	(0.51)	(-0.33)	(-0.82)	(-1.25)
Risk_NA	-0.1563	0.0081	0.0336	-0.0139	-0.1070	-0.0501	-0.0397	-0.0692
	(-9.04)	(0.37)	(1.65)	(-0.78)	(-6.87)	(-2.57)	(-2.26)	(-4.07)
Log (Age estab)	-	-	-	0.0977	-	-	-	0.0551
	-	-	-	(11.94)	-	-	-	(8.67)
Log (Leased space sqft)	0.1737	0.1913	0.1751	0.1918	0.2218	0.1938	0.1765	0.1892
	(25.77)	(18.86)	(24.33)	(32.52)	(34.35)	(20.58)	(28.04)	(41.06)
Log (Wrkrs/sqft leased)	-	-	-	-	0.0343	-0.0151	-0.0223	-0.0182
	-	-	-	-	(7.45)	(-3.38)	(-4.83)	(-5.83)
Headquarters	-	-	-	-	-0.0888	-0.0314	-0.0057	0.0109
	-	-	-	-	(-3.58)	(-1.24)	(-0.36)	(1.31)
Industry NC	-	-	-	-	0.0219	0.1284	0.0870	0.1320
	-	-	-	-	(0.74)	(2.32)	(1.38)	(1.62)
Agriculture	-	-	-	-	0.1762	0.0749	0.1632	0.1816
	-	-	-	-	(3.34)	(1.28)	(2.13)	(4.06)
Mining	-	-	-	-	-0.0445	-0.1192	-0.0351	0.1869
	-	-	-	-	(-0.32)	(-0.68)	(-0.30)	(1.35)
Construction	-	-	-	-	-0.0330	-0.0093	0.0052	-0.0084
	-	-	-	-	(-1.12)	(-0.30)	(0.19)	(-0.39)
Transport & Utilities	-	-	-	-	-0.0203	-0.0510	0.0154	-0.0412
	-	-	-	-	(-0.88)	(-1.03)	(0.59)	(-2.00)
Wholesale	-	-	-	-	0.0393	-0.0196	-0.0025	-0.0189
	-	-	-	-	(1.76)	(-0.78)	(-0.12)	(-1.30)
Retail	-	-	-	-	0.3650	0.2478	0.2085	0.1951
	-	-	-	-	(19.58)	(9.72)	(7.77)	(11.49)
FIRE	-	-	-	-	0.0509	0.0969	0.0935	0.0853
	-	-	-	-	(2.36)	(4.12)	(3.66)	(5.45)
Service	-	-	-	-	0.0857	0.0657	0.0972	0.1098
	-	-	-	-	(5.12)	(3.74)	(5.91)	(9.29)
Government	-	-	-	-	0.1277	0.2862	0.2189	-0.3081
	-	-	-	-	(1.92)	(4.14)	(1.88)	(-1.07)
Observations	33,898	22,021	27,047	50,207	33,898	22,021	27,047	50,207
R-squared	0.154	0.146	0.133	0.210	-	-	-	-
R-squared within	-	-	-	-	0.192	0.165	0.144	0.194
Year lease executed FE	40	40	40	40	40	40	40	40
Age FE	-	3	5	-	-	3	5	-
Zip-code FE	-	-	-	-	1,533	1,384	1,455	1,594

[a] t-ratios in parentheses based on robust standard errors clustered at the zipcode level. Within R-square allows for location fixed effects. Year lease executed fixed effects are entered directly as 1-0 controls. Omitted industry category is manufacturing. Data are from the establishment-level matched CompStak and Dun and Bradstreet establishment level sample

Table 4a: Log Lease Length - New Arrival Versus Renewal Leases with Slope Interactions[a]

	Zipcode Fixed Effect Regression			Building Fixed Effect Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
	New Arrival Lease Coefficients	Renewal Lease Coefficients	Difference in coefficients Col 1-2	New Arrival Lease Coefficients	Renewal Lease Coefficients	Difference in coefficients Col 4-5
Risk_Low	0.0426	0.0111	0.0315	0.0426	0.0134	0.0292
	(4.75)	(0.90)	(2.14)	(4.15)	(1.01)	(1.81)
Risk_Med	0.0198	-0.0143	0.0341	-0.0030	-0.0254	0.0224
	(1.56)	(-0.75)	(1.60)	(-0.23)	(-1.34)	(1.02)
Risk_NA	-0.0860	-0.0570	-0.0290	-0.0782	-0.0871	0.0088
	(-8.31)	(-3.80)	(-1.62)	(-6.88)	(-5.01)	(0.45)
Log (Age estab)	0.0306	0.0546	-0.0241	0.0528	0.0560	-0.0032
	(9.85)	(11.73)	(-4.34)	(21.96)	(12.65)	(-0.66)
Log (Leased space sqft)	0.2016	0.1785	0.0231	0.2046	0.1893	0.0154
	(53.40)	(35.93)	(4.39)	(53.11)	(37.37)	(3.15)
Log (Wrkrs/sqft leased)	0.0008	-0.0120	0.0128	-0.0131	-0.0122	-0.0009
	(0.30)	(-4.05)	(3.46)	(-5.09)	(-3.67)	(-0.22)
Headquarters	-0.0037	0.0004	-0.0041	-0.0082	-0.0054	-0.0028
	(-0.40)	(0.04)	(-0.33)	(-0.93)	(-0.53)	(-0.22)
Industry NC	0.0796	0.0879	-0.0083	0.0401	0.1051	-0.0650
	(2.89)	(1.93)	(-0.17)	(1.55)	(2.03)	(-1.17)
Agriculture	0.1278	0.1781	-0.0503	0.0258	0.0269	-0.0012
	(3.34)	(3.60)	(-0.80)	(0.48)	(0.46)	(-0.02)
Mining	0.0110	0.2440	-0.2330	-0.0776	0.1155	-0.1931
	(0.13)	(1.28)	(-1.13)	(-0.86)	(0.90)	(-1.25)
Construction	-0.0352	-0.0031	-0.0322	-0.0095	0.0508	-0.0602
	(-2.15)	(-0.15)	(-1.34)	(-0.47)	(2.02)	(-2.08)
Transport & Utilities	-0.0326	-0.0299	-0.0027	-0.0343	0.0144	-0.0486
	(-2.44)	(-1.13)	(-0.10)	(-1.99)	(0.57)	(-1.78)
Wholesale	0.0038	-0.0174	0.0211	-0.0094	-0.0015	-0.0078
	(0.35)	(-1.05)	(1.10)	(-0.62)	(-0.07)	(-0.33)
Retail	0.3173	0.2476	0.0698	0.1420	0.1309	0.0111
	(23.08)	(14.06)	(3.58)	(9.28)	(6.17)	(0.46)
FIRE	0.0857	0.0742	0.0115	0.0242	0.0248	-0.0007
	(6.71)	(3.91)	(0.63)	(1.89)	(1.44)	(-0.04)
Service	0.0969	0.0892	0.0078	0.0370	0.0467	-0.0097
	(10.45)	(6.64)	(0.52)	(3.31)	(3.22)	(-0.61)
Government	0.1014	-0.1028	0.2043	0.0336	-0.0135	0.0472
	(2.08)	(-0.37)	(0.73)	(0.57)	(-0.09)	(0.29)
Observations	127,872			127,872		
R-squared within	0.190			0.150		
Year lease executed FE	40			40		
Zip-code FE	1,868			-		
Building FE	-			38,031		

[a] Slope controls are interacted with the New/Renewal status of the lease while restricting the year and location fixed effects to be alike for New and Renewal leases. t-ratios in parentheses based on robust standard errors clustered at the level of the location fixed effects. Within R-square allows for location fixed effects. Year lease executed fixed effects are entered directly as 1-0 controls. Omitted industry category is manufacturing. Data are from the establishment-level matched CompStak and Dun and Bradstreet establishment level sample.

Table 4b: Log Lease Length - New Arrival Versus Renewal Leases with Full Interactions (Slope + Fixed Effects)[a]

	Zipcode Fixed Effect Regression			Building Fixed Effect Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
	New Arrival Lease Coefficients	Renewal Lease Coefficients	Difference in coefficients Col 1-2	New Arrival Lease Coefficients	Renewal Lease Cofficients	Difference in coefficients Col 4-5
Risk_Low	0.0403	0.0133	0.0270	0.0318	0.0254	0.0063
	(4.50)	(1.08)	(1.78)	(2.94)	(1.71)	(0.35)
Risk_Med	0.0116	-0.0060	0.0177	-0.0151	-0.0028	-0.0123
	(0.90)	(-0.34)	(0.80)	(-1.09)	(-0.13)	(-0.48)
Risk_NA	-0.0818	-0.0593	-0.0225	-0.0785	-0.0742	-0.0043
	(-7.89)	(-3.94)	(-1.23)	(-6.59)	(-3.73)	(-0.18)
Log (Age estab)	0.0282	0.0592	-0.0310	0.0506	0.0625	-0.0119
	(9.22)	(12.82)	(-5.60)	(20.30)	(12.21)	(-2.09)
Log (Leased space sqft)	0.2027	0.1759	0.0268	0.2095	0.1842	0.0253
	(52.22)	(34.69)	(4.20)	(49.37)	(30.21)	(3.41)
Log (Wrkrs/sqft leased)	0.0011	-0.0127	0.0139	-0.0120	-0.0105	-0.0015
	(0.42)	(-4.22)	(3.40)	(-4.48)	(-2.76)	(-0.32)
Headquarters	-0.0039	0.0016	-0.0055	-0.0086	-0.0014	-0.0072
	(-0.41)	(0.17)	(-0.41)	(-0.92)	(-0.12)	(-0.49)
Industry NC	0.0590	0.1120	-0.0530	0.0271	0.0822	-0.0551
	(2.16)	(2.43)	(-0.99)	(1.00)	(1.43)	(-0.87)
Agriculture	0.1175	0.1628	-0.0453	0.0297	0.0237	0.0060
	(2.88)	(3.41)	(-0.72)	(0.53)	(0.35)	(0.07)
Mining	-0.0057	0.2820	-0.2878	-0.0672	0.1945	-0.2617
	(-0.07)	(1.46)	(-1.37)	(-0.74)	(1.33)	(-1.52)
Construction	-0.0345	0.0010	-0.0355	-0.0016	0.0604	-0.0620
	(-2.12)	(0.05)	(-1.33)	(-0.07)	(2.00)	(-1.68)
Transport & Utilities	-0.0324	-0.0239	-0.0085	-0.0353	0.0185	-0.0538
	(-2.42)	(-0.97)	(-0.30)	(-1.90)	(0.61)	(-1.51)
Wholesale	0.0041	-0.0153	0.0194	0.0041	-0.0054	0.0095
	(0.38)	(-0.93)	(0.99)	(0.25)	(-0.22)	(0.32)
Retail	0.3083	0.2584	0.0499	0.1385	0.1386	-0.0000
	(22.51)	(14.20)	(2.19)	(8.44)	(5.36)	(-0.00)
FIRE	0.0732	0.0890	-0.0158	0.0163	0.0339	-0.0177
	(5.88)	(4.47)	(-0.67)	(1.18)	(1.63)	(-0.71)
Service	0.0855	0.1016	-0.0161	0.0302	0.0572	-0.0271
	(9.22)	(7.47)	(-0.98)	(2.49)	(3.16)	(-1.24)
Government	0.1023	-0.0934	0.1957	0.0472	0.0205	0.0266
	(2.05)	(-0.33)	(0.69)	(0.74)	(0.15)	(0.18)
Observations	127,872			127,872		
R-squared within	0.182			0.145		
Year lease executed FE	80			80		
Zip-code FE	3,394			-		
Building FE	-			47,966		

[a] These are fully interacted models, with slope controls, year and location fixed effects all interacted with the New/Renewal status of the lease. t-ratios in parentheses based on robust standard errors clustered at the level of the location fixed effects. Within R-square allows for location fixed effects. Year lease executed fixed effects are entered directly as 1-0 contorls. Omitted industry category is manufacturing. Data are from the establishment-level matched CompStak and Dun and Bradstreet establishment level sample.

Table 5: Log Lease Length In the Largest Cities - New York, Los Angeles, and Chicago[a]

	(1)	(2)	(3)	(4)
	Age 5 or less	Age > 10	New Arrival Lease (All Ages)	Renewal Lease (All Ages)
Risk_Low	0.0448	-0.0036	0.0338	0.0050
	(2.18)	(-0.24)	(2.47)	(0.29)
Risk_Med	-0.0085	-0.0248	-0.0025	0.0011
	(-0.27)	(-0.94)	(-0.14)	(0.04)
Risk_NA	-0.0663	-0.0640	-0.0650	-0.0429
	(-3.19)	(-3.26)	(-4.10)	(-1.81)
Log (Age estab)	-	0.0463	0.0294	0.0542
	-	(4.83)	(6.73)	(6.94)
Log (Leased space sqft)	0.1836	0.1895	0.1948	0.1745
	(18.90)	(28.22)	(31.13)	(22.67)
Log (Wrkrs/sqft leased)	0.0055	-0.0160	0.0027	-0.0110
	(1.00)	(-3.46)	(0.67)	(-2.47)
Headquarters	-0.0366	0.0272	0.0182	0.0281
	(-0.99)	(2.09)	(1.72)	(1.75)
Industry NC	0.1208	0.1134	0.1452	0.2043
	(2.58)	(1.07)	(3.22)	(2.62)
Agriculture	0.0554	0.2001	0.0314	0.1953
	(0.77)	(3.35)	(0.38)	(2.62)
Mining	-0.0303	0.3256	0.0511	0.4376
	(-0.17)	(2.28)	(0.40)	(2.16)
Construction	-0.0802	0.0394	-0.0146	-0.0174
	(-2.11)	(1.24)	(-0.56)	(-0.48)
Transport & Utilities	-0.0880	-0.0213	-0.0176	-0.0561
	(-1.81)	(-0.71)	(-0.82)	(-1.33)
Wholesale	-0.0231	-0.0076	0.0087	-0.0359
	(-0.76)	(-0.32)	(0.47)	(-1.34)
Retail	0.2841	0.2015	0.2960	0.2438
	(10.82)	(7.43)	(14.51)	(8.86)
FIRE	0.0017	0.0675	0.0438	0.0419
	(0.06)	(2.87)	(2.36)	(1.30)
Service	0.0368	0.1194	0.0851	0.0955
	(1.65)	(6.41)	(5.40)	(4.17)
Government	0.2721	-0.0495	0.1120	0.2359
	(4.20)	(-0.31)	(0.92)	(2.29)
Observations	22,353	22,460	31,132	22,682
R-squared within	0.176	0.210	0.208	0.171
Year lease executed FE	40	40	40	40
Age FE	5	-	-	-
Zip-code FE	592	564	590	598

[a] t-ratios in parentheses based on robust standard errors clustered at the zipcode level. Within R-square allows for zipcode fixed effects. Year lease executed fixed effects are entered directly as 1-0 controls. Omitted industry category is manufacturing. Data are from the establishment-level matched CompStak and Dun and Bradstreet establishment level sample.

Table 6: Term Structure (Log Lease Rate/sqft)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS Zipcode Density Max Samp	OLS Zipcode Density	Zipcode FE and Controls	Low Risk with ZFE	Medium and High Risk with ZFE	Bldng FE and Controls	Low Risk with BFE	Medium and High Risk with BFE
Log(Emp/sqmi zip)	0.1389	0.1628	-	-	-	-	-	-
	(5.94)	(6.63)	-	-	-	-	-	-
Risk_Low	0.2579	0.3923	0.1913	-	-	0.0946	-	-
	(6.27)	(6.10)	(4.32)	-	-	(3.34)	-	-
Log(lease length)	0.2013	0.2060	0.1910	0.1386	0.1917	0.0931	0.0684	0.0786
	(13.26)	(10.79)	(15.42)	(18.22)	(16.07)	(13.28)	(15.35)	(7.70)
Risk_Low*Log(LL)	-0.0650	-0.0988	-0.0488	-	-	-0.0238	-	-
	(-6.28)	(-5.98)	(-4.23)	-	-	(-3.30)	-	-
Log(Age Estab)	-	-	-0.0333	-0.0305	-0.0408	-0.0054	-0.0034	-0.0118
	-	-	(-11.06)	(-9.14)	(-7.58)	(-3.07)	(-1.81)	(-2.18)
Log (Leased space)	-	-	-0.0494	-0.0429	-0.0665	-0.0159	-0.0148	-0.0189
	-	-	(-5.98)	(-5.16)	(-6.51)	(-4.73)	(-4.08)	(-2.43)
Log (wrkrs/sqft)	-	-	0.0243	0.0248	0.0212	0.0037	0.0058	0.0031
	-	-	(6.71)	(6.48)	(3.82)	(2.08)	(2.87)	(0.67)
Ground Level	-	-	-0.0346	-0.0417	0.0016	0.0575	0.0461	0.1295
	-	-	(-1.58)	(-2.08)	(0.04)	(6.53)	(4.88)	(4.73)
Log(Floor Number)	-	-	0.0307	0.0401	0.0077	0.0321	0.0410	0.0071
	-	-	(3.04)	(3.45)	(0.52)	(4.90)	(5.49)	(0.59)
Headquarters	-	-	0.0514	0.0492	0.0402	-0.0001	-0.0029	0.0063
	-	-	(5.85)	(5.53)	(2.35)	(-0.02)	(-0.54)	(0.41)
Industry NC	-	-	0.1392	0.1480	0.0680	0.0395	0.0055	0.0519
	-	-	(1.98)	(1.91)	(0.50)	(0.67)	(0.05)	(0.55)
Agriculture	-	-	0.0119	-0.0007	0.0441	0.0356	0.0150	0.0408
	-	-	(0.28)	(-0.02)	(0.55)	(1.22)	(0.49)	(0.51)
Mining	-	-	0.2601	0.0749	0.4164	0.0608	-0.0409	-0.0275
	-	-	(4.64)	(0.99)	(5.60)	(1.25)	(-0.77)	(-0.69)
Construction	-	-	-0.0776	-0.0834	-0.0675	-0.0065	0.0034	-0.0598
	-	-	(-3.69)	(-3.59)	(-2.03)	(-0.52)	(0.22)	(-1.76)
Transport & Utilities	-	-	0.0253	0.0145	0.0312	-0.0132	-0.0125	-0.0690
	-	-	(1.04)	(0.51)	(1.08)	(-0.94)	(-0.72)	(-1.99)
Wholesale	-	-	-0.0360	-0.0385	-0.0325	-0.0139	-0.0152	-0.0446
	-	-	(-2.28)	(-2.09)	(-1.26)	(-1.31)	(-1.18)	(-1.60)
Retail	-	-	0.2166	0.2128	0.2099	0.0800	0.0810	0.0560
	-	-	(9.24)	(8.34)	(7.01)	(5.45)	(4.73)	(1.47)
FIRE	-	-	0.1735	0.1745	0.1634	0.0105	0.0104	-0.0244
	-	-	(8.79)	(8.50)	(5.54)	(1.18)	(1.01)	(-0.94)
Service	-	-	0.1024	0.1044	0.0932	-0.0049	-0.0065	-0.0392
	-	-	(6.65)	(6.27)	(3.85)	(-0.61)	(-0.69)	(-1.68)
Government	-	-	0.1892	0.2113	0.1617	-0.0058	-0.0090	0.0707
	-	-	(3.34)	(3.49)	(1.96)	(-0.23)	(-0.33)	(0.76)
Observations	139,757	62,571	62,571	48,099	14,472	62,571	48,099	14,472
R-squared	0.244	0.278	-	-	-	-	-	-
R-squared within	-	-	0.260	0.263	0.271	0.315	0.333	0.298
Year lease exec FE	40	37	37	37	36	37	37	34
Zipcode FE	-	-	1,529	1,436	1,105	-	-	-
Building FE	-	-	-	-	-	19,489	15,779	7,478

[a] t-ratios based on robust standard errors clustered at the zipcode level in columns 1-5 and at the building level in columns 6-8. Omitted industry category is manufacturing. Within R-square allows for location fixed effects. Year lease executed fixed effects are entered directly as 1-0 controls. Observations for which Risk is NA are omitted.

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Appendix A: Comparative Statics

This appendix derives the comparative-static derivatives mentioned in the text. Totally differentiating (6) yields

$$(1+\delta-\delta F^g-\delta r^g f^g)dr^g \;+\; \delta r^g f^g dk^g \;-\; \delta dk^b \;=\; 0, \qquad (a1)$$

where $f^g = f(r^g - p_0 - k^g)$. For stability of the equilibrium, an increase in r^g should raise the difference between $\Pi_{LT}(r^g)$ and $\Pi_{ST}(r^g)$, which implies that the dr^g term in $(a1)$ should be positive. Using $(a1)$, the comparative-static derivatives are then

$$\frac{\partial r^g}{\partial k^g} \;=\; \frac{\delta r^g f^g}{1+\delta-\delta F^g-\delta r^g f^g} \;>\; 0. \qquad (a2)$$

$$\frac{\partial r^g}{\partial k^b} \;=\; \frac{\delta}{1+\delta-\delta F^g-\delta r^g f^g} \;>\; 0. \qquad (a3)$$

Since the denominator of $(a3)$ is positive, $\partial r^g/\partial k^b < 1$ holds when $\delta < 1+\delta-\delta F^g-\delta r^g f^g$ or $0 < 1-\delta F^g-\delta r^g f^g$. This inequality is not guaranteed to hold, but consider the expression $\delta r^g(1-F^g)$, equal to the present value of the landlord's LT revenue in the second period, which should be increasing in r^g despite the fact that a higher r^g raises the chance of default. The derivative of this expression is $\delta-\delta F^g-\delta r^g f^g$, and its positivity implies positivity of $1-\delta F^g-\delta r^g f^g$, ensuring $\partial r^g/\partial k^b < 1$.