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 an equilibrium 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 an equilibrium.

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]

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, of course, 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 provide 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. (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

[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.

simulation, confirming 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 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

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[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 (2023), 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.

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 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

[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.
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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.

In order to pin down the levels of both ST and LT rents in the model, we make some strong and unconventional assumptions that are needed because more-conventional approaches are not workable, as explained below. 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, we assume that rent on a long-term contract is set to yield 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 types of contracts, preventing an outcome where only one type is provided. This equal-profit assumption is similar to a more-conventional assumption that the EPV of profit is zero for each contract type, but that assumption turns out to be unworkable in our setting.[12]

Our assumptions do not necessarily match outcomes that would arise in a free-market setting. But they can be generated by assuming a single monopoly landlord who sets ST rents to fully extract tenant revenue, but who faces rent regulation that requires long-term contracts to generate the same EPV of profit as ST contracts. This is environment is not very realistic, but it lends some plausibility to our assumptions.

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, despite being nonstandard, 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.[13]

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[12] See footnote 13 below for details.

[13] In place of our maintained assumptions, suppose that competition existed among multiple landlords, driving the

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

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

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

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).[14] In addition to 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 equilibrium 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

EPV profit to zero for each contract type. Then ST rents would equal the land's cost, c, introduced below. In order for the ST rent in period 1 to be affordable under all circumstances, the lowest possible revenue for tenant type i, equal to $p_0 + k^i + \underline{\epsilon}$ must then exceed c. But it is easily seen that this condition in turn implies that default under a zero-profit LT contract will never occur. These observations show the difficulty of using a conventional approach to analyze our problem.

[14] 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.

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

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.[15] 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.[16]

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

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

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

[16] 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 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.

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, as required in equilibrium, 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 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 $k^b > 0$.[17]

[17] Note that, even though rent then exceeds revenue in period 0, the incentive for default is absent as long as the

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 an equilibrium, 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:

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

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.*

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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.

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[18]

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

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.[19]

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 $\bar{\epsilon}$ 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).[20] 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 the equilibrium assignment is that, with default protecting the tenant from the downside of low 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.

Even though landlords have been assumed to know tenant types, the assignment characterized in Proposition 1 would still be an equilibrium if tenant types were unobserved, being

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[18] 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).

[19] 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.

[20] 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.

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 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

[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.

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 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 spelling 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 early 1990s. 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 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

[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.

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 (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/sqmile 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,

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

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 (2023), 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 relationship.

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.

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

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.

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 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 building manager'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**). In many of the specifications, this variable is used to split observations into subsamples of new and renewal tenants. 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. Stratifying sample by new and renewal tenants effectively interacts lease type with all other controls in the model including location fixed effects, analogous to the age-stratified regressions described above. This approach allows for many other possible unobserved drivers of lease rates and helps to ensure reliable estimates of the difference in coefficients on the risk measures when comparing the two sets of lease records.[27]

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.

Other 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.

[27] It is worth noting, as an example, 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. Stratifying the models into new and renewal leases does much to address differences between these two groups of establishments and especially so if there are any differences in location given the location fixed effects included in most of the models.

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 are 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 and the control for space leased (**Log(Space leased sqft)**). 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 statistically significant elasticity of 0.19. That tenants who occupy substantial floor space receive long leases (as seen in the significant coefficient) 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 significantly 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, 4.73% and 3.86% 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 -5.5% 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 0.16 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 4.73% to 4.41%, the **Risk_Med** effect rising from 3.86% to 4.58%, and the **Risk_NA** coefficient shrinking from -5.5% to -4.8%. 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.[28]

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 positive and significant 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.

[28] 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.

Turning to the SIC 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 29% and 25% longer, respectively. In all three industries, the lease length premium is also highly significant. By contrast, lease length is more similar to manufacturing in most of the other industries seen in the table.

Column 4 adds zip-code employment density, **Log(Emp/sqmi zipcode)**, which has a positive effect on lease length: the lease-length elasticity is 5.9%, consistent with tenants valuing densely developed locations with potential to yield benefits from other nearby economic activity. The presence of employment density tends to mute the effect of most of the other variables whose coefficients are significant (reducing their absolute values), but the overall change is modest except for the crowding coefficient on **Log(Wrkrs/sqft leased)** which is much smaller and no longer significant. For the measures of primary interest, the **Risk_Med** coefficient becomes notably smaller and insignificant, but the **Risk_Low** coefficient remains significant and close to the value in column 2, while 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 becomes somewhat smaller but remains significant, while many other coefficients become even smaller in absolute value, reinforcing their previous changes (the age and headquarters coefficients become insignificant). The effect of zip-code employment density becomes insignificant.

Column 6 shows the effects of adding zip-code fixed effects while dropping the zip-code employment-density variable, and the results are mostly similar to those in column 4. Column 7 illustrates the effects of adding 38,031 fixed effects for individual buildings, the narrowest geographic control. The **Risk_Low** coefficient remains significant and nearly identical in size to its values under city and zip-code fixed effects. In contrast to the results in columns 1-4, which showed a 3.5-4.7% longer lease length for low-risk tenants, columns 5-7 indicate that the leases of these tenants are about 2.9% longer than those of high-risk tenants. The effect of establishment age regains significance in column 7, being larger than the values in columns 1-3 (the elasticity of lease length with respect to age is 1.4%). Bearing in mind that the building fixed-effect model controls for choice of building and all of its attributes, this estimated age effect is consistent with the argument that more established companies are better able to anticipate future space needs and seek longer leases so as to reduce future relocation costs.

Mirroring that pattern, the **Log(Wrkrs/sqft leased)** coefficient in column 7 becomes negative and significant, in contrast to the previous columns. 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. In addition, the coefficients for the Retail, FIRE and Service SIC codes remain significant with their previously estimated signs, but the magnitudes of the coefficients are smaller than in previous columns.

4.2. Stratification by age

To gain a fuller sense of the interaction between firm age and the risk measures in determining lease length, Table 3 presents regressions stratified by age categories: firms 1 year old, 2-5 years old, 6-10 years old, and older than 10 years. Within the second and third age ranges, the firm's age level is captured by fixed effects (see bottom of 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, space leased and age, while the second group also includes all of 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 with one especially sharp difference for established companies beyond 10 years in age. Notice, for example, that, for all of the models in Table 3, the elasticity of lease length with respect to space leased is approximately 19%, close to the estimates in Table 2. For firms 1 through 10 years in age (columns 1-3) the **Risk_Low** coefficient is always positive and significant, as in Table 2. Also largely as in Table 2, the coefficients on **Risk_Med** are positive and mostly significant in the restricted models (columns 1-3) but smaller in magnitude and not significant when the full set of covariates is added to the model (in columns 5-7).

The pattern for the **Risk_NA** coefficients in Table 3 differs somewhat from Table 2. For newly created establishments (Age = 1), the coefficients in the restricted and fully specified models (columns 1 and 5) are both negative and highly significant, with much larger coefficients than for the other age groups. Apart from a general awareness that half of newly created companies fail in their first five years, it is plausible that landlords often have limited information on the reliability of a newly created company. It is plausible that, in instances where D&B does not have sufficient information to assign a risk assessment, such establishments are viewed as high-risk, as implied by the large negative coefficient on **Risk_NA**: -10% in the fully specified model in column (5).

The most striking difference between Tables 3 and 2 is for establishments over 10 years in age. For this group, the estimates in Table 3 indicate that both of the D&B **Risk_Low** and **Risk_Med** measures have little predictive power in determining lease length. This outcome seems likely to arise because most seasoned companies have track records that can be readily verified by a landlord, making the D&B risk assessment measure obsolete. On the other hand, when information is not sufficiently available to evaluate risk, we would expect landlords to be cautious and to view such establishments as high-risk. That view may explain the -5.5% and highly significant coefficient on **Risk_NA** in column 8.

The remaining pattern in column 8 that warrants comment is the coefficient on log age, which is large, positive, and highly significant in both the restricted and fully-specified models in columns 4 and 8: for the latter, the elasticity of lease length with respect to age is 5.3%. Recall also that the D&B risk score is based on a company's age, whether it is a corporation, the presence of active lawsuits, liens or judgements, the company's net worth, and trade data. That structure along with the small and insignificant coefficient on **Risk_Low** suggests that something other than risk is driving the effect of age in column 8. One possible mechanism that seems especially plausible is that, as companies become ever more established, their future space needs become more stable, which contributes to preference for a longer lease.[29]

4.3. Renewal vs. new tenants

Comparing lease renewals to leases extended to new tenants provides a different opportunity to demonstrate that building managers take risk into account when writing lease contracts. Because landlords do not have a prior history with a new tenant, we believe that new tenants are likely to be viewed by landlords as riskier than existing tenants who are renewing a lease. To allow for this and other possible differences between new and lease-renewal

[29] Note that the 0.0441 **Risk_Low** coefficient in column 2 of Table 2 can be viewed as a blend of the corresponding coefficients in columns 1-4 of Table 3.

observations, Table 4 divides the sample into "New Arrival" and "Renewal" subsamples, running the zip-code and building-fixed-effect regressions from Table 2 on the two subsamples. In this instance, all age groups are always pooled together.

Overall, stratifying samples into **Renewal** and **New** contracts yields results that echo patterns from the age-stratified regressions described above. In column 1, which pertains to new tenants and uses zip-code fixed effects, the **Risk_Low** coefficient continues to be significant and has a larger magnitude than before, showing a 4.1% increase in lease length relative to high-risk tenants. But in column 2, which shows results for renewal tenants, the **Risk_Low** coefficient is much smaller and insignificant along with that of **Risk_Med**, showing that among renewal tenants, the risk measures are irrelevant in determining lease length. 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 analogous to the discussion of Table 3, firm age continues to have a significantly positive effect on lease length regardless of tenant type. This pattern once again suggests that the non-age risk factors used to create the D&B risk measure have no role in determining lease length for existing tenants.

Evidently, based on prior experience, existing tenants who are renewing a lease are viewed as safe bets by landlords regardless of how D&B classifies their riskiness. By contrast, the risk measure matters for new tenants, who have no track record with the landlord.[30] These results show that the previous positive and significant **Risk_Low** coefficients in Table 2 were a blend of a positive effect for new tenants and a near-zero effect for existing tenants, with the positive effect dominating. As for the other control variables, the signs and significance levels of their coefficients are mostly the same as those in column 5 of Table 2. The main exception is for the crowding coefficient, which is insignificant for new tenants (column 1) and significantly negative for renewals (column 2).

Columns 3 and 4 of Table 4, which use building fixed effects, show the same qualitative risk-coefficient patterns as in columns 1 and 2, with the **Risk_Low** coefficient significantly positive for new tenants while notably smaller and insignificant for renewal tenants. Therefore, with even finer geographic controls, the risk measures are again only relevant for new tenants.

[30] Panel A of appendix Table B-1 shows that the risk measures for new and renewal tenants are actually very similar, with low-risk shares being only slightly lower for new tenants (0.54 vs. 0.69). Apparently, the risk information for renewal tenants is superseded by the actual experiences of the landlord, whereas the information is important in assessing risk attributes among new tenants.

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, distinguishing between young (ages up to five years) and old (age above 10 years) tenants and between new tenants and renewal tenants, while using zip-code fixed effects. The sample sizes are cut by about half for each group under this big-city restriction. The table shows exactly the same risk-coefficient pattern as before, with the **Risk_Low** coefficient significantly positive for young tenants and insignificant for old tenants, and significantly positive for new tenants and insignificant for renewal tenants. Firm age continues to exert a positive effect across all tenants types.

The effects of the main controls are similar to those in Table 4. As an example, the **Retail** coefficient, which was strongly positive and significant in Tables 1 and 2, remains so in the three largest cities across all the regressions. Overall, Table 5 mostly confirms the previous findings on risk effects, showing that the D&B risk variables are relevant only for new and younger tenants.

5. Term-structure regressions

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 using option-based models and numerical simulation. Their numerical 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 empirical work carried out by Ambrose and Yildirim (2008) and Ambrose et al. (2011) and providing evidence in support of the simulation results from these two significant previous papers.[31]

We estimate the term-structure/risk relationship in a series of lease-rate regressions presented in Tables 6 and 7. 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

[31] 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.

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 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 as the only other control apart from the risk and lease-length measures and is estimated using the largest sample possible, with 139,757 observations. Column (2) repeats this regression restricting the sample to just those observations for models reported elsewhere in the table, having 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), the lease rate increases significantly with nearby employment density, with elasticities of 13.5% and 15.3% in columns 1 and 2, respectively. The **Risk_Low** coefficients are both positive and highly significant, consistent with expectations that lower-risk tenants occupy higher quality suites. The elasticity of the lease rate with respect to lease length is roughly 18% in both regressions, consistent with the upward sloping pattern that was anticipated, and is again significant. Most important, the interaction terms are negative and highly significant. The elasticity difference is roughly 7% in column (1) and 10% in column (2). These estimates confirm the prediction of Ambrose and Yildirim (2008) and Agrawal et al. (2011) that the rental term structure is steeper for risky tenants.

Column (3) adds additional controls to address possible unobserved factors. Local employment density is replaced with over 1,500 zipcode fixed effects that capture a wide range of neighborhood attributes. Other controls include establishment age, space leased, crowding, and controls to 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) help to explain variation in rent and perform mostly as anticipated. Rents rise slightly with firm 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 risky and low-risk elasticities again support the main hypothesis, equaling 16.2% and 10.3%, respectively.

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 as before, and importantly, estimates of the low- and high-risk term structure coefficients are little changed. Columns 4 and 5 show that, with zip-code fixed effects, rent rises almost twice as fast with lease length for risky tenants as for low-risk tenants (elasticities are 16.6% vs. 9.8%, 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: the corresponding elasticities associated with lease length for low-risk (column 7) and risky (column 8) tenants are 4.4% and 2.6%, respectively. Once again, term structure is flatter for low-risk tenants.

Table 7 repeats the fixed-effect regression in column 3 of Table 6 on subsamples stratified by age. The question addressed is whether the term-structure effects seen in that regression hold in different age groups. Columns 1-4, which use zip-code fixed effects, show an upward-sloping term structure for risky tenants across all age groups. But its steepness falls with age, showing that the riskiness component of age is a separate determinant of the term structure beyond non-age factors that influence **Risk_Low**. As for the interaction coefficients, their signs are all negative, but only the coefficient for age-1 firms is significant, indicating a 0.0451 low-risk reduction in the rent elasticity relative to the risky tenant value of 0.2731. Like the decline in the risky lease-length coefficient for higher age categories, this pattern again shows the waning importance of the D&B risk measure as a term-structure determinant as rising age makes tenants less risky. The pattern for the lease-length and interaction coefficients in the regressions that use building fixed effects (columns 5-8) show exactly the same pattern.

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 no 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. 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. Since bad tenant behavior (such as making late payments or default) has a greater chance of occurring over a longer contract, landlords will require a higher rent premium (beyond any compensation for inflation risk) when renting long-term to a risky tenant. The observed rent premium earned on long-term leases under the observed term structure is then 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/sqft zipcode)	-	-	-	0.0591	0.0027	-	-
	-	-	-	(11.92)	(0.26)	-	-
Risk_Low	0.0473	0.0441	0.0396	0.0340	0.0299	0.0288	0.0287
	(4.87)	(4.55)	(4.27)	(3.78)	(2.29)	(3.57)	(3.29)
Risk_Med	0.0386	0.0458	0.0348	0.0151	0.0038	0.0022	-0.0161
	(0.2.75)	(3.41)	(2.75)	(1.19)	(0.19)	(0.17)	(-1.41)
Risk_NA	-0.0553	-0.0482	-0.0440	-0.0631	-0.0620	-0.0604	-0.0582
	(-5.04)	(-4.50)	(-4.13)	(-6.22)	(-7.11)	(-6.77)	(-5.76)
Log (Age estab)	-	0.0103	0.0117	0.0071	-0.0008	-0.0001	0.0144
	-	(3.06)	(3.21)	(2.05)	(-0.23)	(-0.04)	(6.95)
Log (Leased space sqft)	0.1908	0.1897	0.2059	0.1850	0.1929	0.1992	0.2077
	(31.18)	(31.67)	(43.30)	(44.68)	(39.54)	(53.28)	(54.26)
Log (Wrkrs/sqft leased)	-	-	0.0082	0.0022	0.0019	0.0007	-0.0059
	-	-	(2.64)	(0.74)	(0.71)	(0.28)	(-2.62)
Headquarters	-	-	0.0363	0.0186	0.0065	0.0047	0.0021
	-	-	(3.81)	(2.25)	(0.75)	(0.62)	(0.28)
Industry NC	-	-	0.2123	0.1474	0.0741	0.0542	0.0187
	-	-	(6.36)	(4.81)	(2.52)	(2.20)	(0.78)
Agriculture	-	-	0.2724	0.2765	0.1798	0.1505	0.0286
	-	-	(6.82)	(6.67)	(5.19)	(4.94)	(0.70)
Mining	-	-	0.2666	0.1727	0.1268	0.1291	0.0049
	-	-	(1.66)	(1.22)	(1.24)	(1.07)	(0.06)
Construction	-	-	-0.0056	0.0041	-0.0226	-0.0214	0.0115
	-	-	(-0.30)	(0.23)	(-1.54)	(-1.48)	(0.65)
Transport & Utilities	-	-	0.0251	-0.0019	-0.0330	-0.0408	-0.0193
	-	-	(1.52)	(-0.12)	(-1.69)	(-2.47)	(-1.19)
Wholesale	-	-	0.0076	0.0003	-0.0053	-0.0036	-0.0015
	-	-	(0.58)	(0.02)	(-0.55)	(-0.36)	(-0.11)
Retail	-	-	0.4408	0.4098	0.3223	0.2861	0.1337
	-	-	(24.97)	(24.17)	(22.45)	(23.06)	(9.76)
FIRE	-	-	0.2919	0.1832	0.1063	0.0808	0.0254
	-	-	(14.70)	(10.52)	(3.88)	(6.02)	(2.13)
Service	-	-	0.2500	0.1761	0.1170	0.0916	0.0401
	-	-	(18.48)	(13.81)	(8.00)	(10.25)	(3.91)
Government	-	-	0.2236	0.1361	0.0368	-0.0001	0.0046
	-	-	(1.65)	(0.98)	(0.24)	(-0.00)	(0.06)
Observations	127,872	127,872	127,872	127,871	127,871	127,872	127,872
R-squared	0.160	0.161	0.194	0.226	0.168	0.170	0.124
Zip-code FE	-	-	-	-	-	1,868	-
Building FE	-	-	-	-	-	-	38,031
City FE	-	-	-	-	1,045	-	-

[a] t-ratios in parentheses based on robust standard errors clustered at the level of the fixed effects in columns 4-6 (city, zip code or building). 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 = 1	Age 2-5	Age 6-10	Age > 10	Age = 1 Zip FE	Age 2-5 Zip FE	Age 6-10 Zip FE	Age > 10 Zip FE
Risk_Low	0.0449	0.0801	0.0615	0.0094	0.0294	0.0425	0.0265	0.0045
	(2.67)	(4.48)	(3.77)	(0.57)	(1.90)	(2.58)	(1.76)	(0.33)
Risk_Med	0.0292	0.0481	0.0536	-0.0173	0.0097	-0.0205	-0.0254	-0.0307
	(1.52)	(1.69)	(2.04)	(-0.77)	(0.53)	(-0.70)	(-1.12)	(-1.55)
Risk_NA	-0.1666	0.0180	0.0438	-0.0055	-0.0998	-0.0271	-0.0230	-0.0555
	(-9.50)	(0.81)	(2.39)	(-0.30)	(-6.45)	(-1.38)	(-1.31)	(-3.23)
Log (Age estab)	-	-	-	0.1031	-	-	-	0.0532
	-	-	-	(12.61)	-	-	-	(8.34)
Log (Leased space sqft)	0.1732	0.1931	0.1768	0.1966	0.2237	0.2013	0.1821	0.1944
	(24.74)	(18.47)	(23.45)	(31.64)	(35.50)	(21.03)	(28.17)	(41.49)
Log (Wrkrs/sqft leased)	-	-	-	-	0.0347	-0.0068	-0.0142	-0.0127
	-	-	-	-	(7.60)	(-1.58)	(-3.20)	(-4.09)
Headquarters	-	-	-	-	-0.0859	-0.0237	0.0011	0.0130
	-	-	-	-	(-3.37)	(-0.91)	(0.07)	(1.56)
Industry NC	-	-	-	-	0.0141	0.0838	0.0351	0.0500
	-	-	-	-	(0.48)	(1.56)	(0.56)	(0.55)
Agriculture	-	-	-	-	0.1709	0.0675	0.1629	0.1795
	-	-	-	-	(3.24)	(1.15)	(2.13)	(3.93)
Mining	-	-	-	-	-0.0475	-0.1330	-0.0415	0.2137
	-	-	-	-	(-0.34)	(-0.75)	(-0.36)	(1.38)
Construction	-	-	-	-	-0.0359	-0.0105	0.0015	-0.0126
	-	-	-	-	(-1.21)	(-0.34)	(0.06)	(-0.59)
Transport & Utilities	-	-	-	-	-0.0238	-0.0578	0.0123	-0.0507
	-	-	-	-	(-1.03)	(-1.14)	(0.47)	(-2.44)
Wholesale	-	-	-	-	0.0350	-0.0174	-0.0028	-0.0184
	-	-	-	-	(1.59)	(-0.70)	(-0.13)	(-1.23)
Retail	-	-	-	-	0.3608	0.2419	0.2046	0.1881
	-	-	-	-	(19.30)	(9.28)	(7.75)	(11.01)
FIRE	-	-	-	-	0.0490	0.0968	0.0971	0.0867
	-	-	-	-	(2.26)	(4.13)	(3.88)	(5.46)
Service	-	-	-	-	0.0827	0.0631	0.0973	0.1088
	-	-	-	-	(4.92)	(3.52)	(5.97)	(9.10)
Government	-	-	-	-	0.1291	0.2706	0.2018	-0.3272
	-	-	-	-	(1.94)	(3.74)	(1.70)	(-1.08)
Observations	33,898	22,021	27,047	50,207	33,898	22,021	27,047	50,207
R-squared	0.149	0.142	0.127	0.194	0.189	0.160	0.139	0.182
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 zip level. Omitted industry category is manufacturing. Data are from the establishment-level matched CompStak and Dun and Bradstreet establishment level sample

Table 4: Log Lease Length - New Arrival Tenant Leases Versus Renewals[a]

	(1) New Arrival Lease Zip-code FE	(2) Renewal Lease Zip-code FE	(3) New Arrival Lease Bldg FE	(4) Renewal Lease Bldg FE
Risk_Low	0.0408	0.0118	0.0331	0.0248
	(4.51)	(0.96)	(3.06)	(1.65)
Risk_Med	0.0117	-0.0144	-0.0144	-0.0094
	(0.89)	(-0.78)	(-1.04)	(-0.43)
Risk_NA	-0.0745	-0.0467	-0.0620	-0.0554
	(-7.14)	(-3.16)	(-5.26)	(-2.78)
Log (Age estab)	0.0250	0.0516	0.0455	0.0519
	(8.51)	(11.03)	(18.86)	(10.10)
Log (Leased space sqft)	0.2049	0.1813	0.2139	0.1911
	(52.54)	(35.58)	(51.00)	(31.23)
Log (Wrkrs/sqft leased)	0.0025	-0.0061	-0.0099	-0.0019
	(0.91)	(-2.04)	(-3.73)	(-0.50)
Headquarters	-0.0029	0.0052	-0.0075	0.0034
	(-0.31)	(0.53)	(-0.81)	(0.30)
Industry NC	0.0510	0.0781	0.0053	0.0349
	(1.91)	(1.72)	(0.19)	(0.62)
Agriculture	0.1121	0.1623	0.0272	0.0148
	(2.72)	(3.27)	(0.48)	(0.22)
Mining	-0.0064	0.3152	-0.0712	0.2018
	(-0.08)	(1.47)	(-0.78)	(1.36)
Construction	-0.0356	-0.0010	-0.0052	0.0558
	(-2.19)	(-0.05)	(-0.25)	(1.85)
Transport & Utilities	-0.0354	-0.0270	-0.0368	0.0121
	(-2.62)	(-1.08)	(-1.95)	(0.39)
Wholesale	0.0021	-0.0125	0.0040	-0.0050
	(0.20)	(-0.76)	(0.25)	(-0.20)
Retail	0.3051	0.2571	0.1358	0.1341
	(22.07)	(14.04)	(8.26)	(5.17)
FIRE	0.0731	0.0929	0.0162	0.0366
	(5.79)	(4.62)	(1.18)	(1.75)
Service	0.0841	0.1036	0.0281	0.0590
	(9.00)	(7.56)	(2.31)	(3.24)
Government	0.1006	-0.1041	0.0430	0.0051
	(2.02)	(-0.37)	(0.67)	(0.04)
Observations	72,283	55,589	72,283	55,589
R-squared	0.205	0.147	0.168	0.103
Zip-code FE	1,669	1,725	-	-
Building FE	-	-	27,471	20,495

[a] t-ratios in parentheses based on robust standard errors clustered at the level of the fixed effects (zip code or building). 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	-0.0037	0.0346	0.0041
	(2.17)	(-0.24)	(2.46)	(0.24)
Risk_Med	-0.0113	-0.0283	-0.0029	-0.0064
	(-0.36)	(-1.03)	(-0.15)	(-0.25)
Risk_NA	-0.0483	-0.0508	-0.0530	-0.0280
	(-2.34)	(-2.65)	(-3.25)	(-1.19)
Log (Age estab)	-	0.0445	0.0245	0.0462
	-	(4.64)	(5.90)	(5.73)
Log (Leased space sqft)	0.1893	0.1960	0.1975	0.1820
	(20.25)	(27.89)	(31.40)	(22.85)
Log (Wrkrs/sqft leased)	0.0099	-0.0106	0.0052	-0.0037
	(1.84)	(-2.32)	(1.29)	(-0.82)
Headquarters	-0.0322	0.0320	0.0210	0.0347
	(-0.85)	(2.45)	(1.94)	(2.17)
Industry NC	0.0897	-0.0059	0.1253	0.1527
	(1.92)	(-0.04)	(2.81)	(1.95)
Agriculture	0.0473	0.1883	0.0253	0.1784
	(0.64)	(3.20)	(0.30)	(2.38)
Mining	-0.0182	0.3702	0.0590	0.5017
	(-0.10)	(2.20)	(0.45)	(2.15)
Construction	-0.0831	0.0235	-0.0192	-0.0277
	(-2.18)	(0.72)	(-0.74)	(-0.75)
Transport & Utilities	-0.0926	-0.0347	-0.0232	-0.0660
	(-1.87)	(-1.15)	(-1.07)	(-1.52)
Wholesale	-0.0291	-0.0120	0.0052	-0.0407
	(-0.95)	(-0.48)	(0.28)	(-1.51)
Retail	0.2773	0.1919	0.2903	0.2345
	(10.54)	(7.01)	(14.31)	(8.21)
FIRE	0.0009	0.0669	0.0437	0.0395
	(0.03)	(2.78)	(2.39)	(1.20)
Service	0.0342	0.1171	0.0828	0.0932
	(1.51)	(6.11)	(5.23)	(3.91)
Government	0.2624	-0.0720	0.1067	0.2142
	(3.95)	(-0.44)	(0.88)	(2.03)
Observations	22,353	22,460	31,132	22,682
R-squared	0.176	0.210	0.208	0.171
Age FE	5	-	-	-
Zip-code FE	592	564	590	598

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
Risk_Low	0.2919	0.4307	0.2276	-	-	0.1171	-	-
	(6.88)	(6.36)	(4.62)	-	-	(3.54)	-	-
Log(lease length)	0.1875	0.1761	0.1623	0.0979	0.1664	0.0594	0.0260	0.0441
	(11.91)	(8.74)	(11.52)	(11.14)	(10.37)	(7.30)	(4.60)	(3.74)
Risk_Low*Log(LL)	-0.0726	-0.1060	-0.0596	-	-	-0.0308	-	-
	(-6.83)	(-6.16)	(-4.77)	-	-	(-3.68)	-	-
Log (Emp/sqft zipcd)	0.1349	0.1530	-	-	-	-	-	-
	(5.69)	(6.11)	-	-	-	-	-	-
Log(Age Estab)	-	-	0.0102	0.0104	0.0174	0.0347	0.0342	0.0509
	-	-	(3.44)	(3.24)	(2.56)	(16.93)	(15.57)	(8.15)
Log (Leased space)	-	-	-0.0664	-0.0555	-0.1003	-0.0297	-0.0254	-0.0456
	-	-	(-7.48)	(-6.26)	(-8.65)	(-7.73)	(-6.09)	(-5.39)
Log (wrkrs/sqft)	-	-	0.0041	0.0069	-0.0094	-0.0143	-0.0105	-0.0259
	-	-	(1.04)	(1.71)	(-1.42)	(-6.27)	(-4.04)	(-4.73)
Ground Level	-	-	-0.0390	-0.0447	-0.0070	0.0573	0.0461	0.1316
	-	-	(-1.61)	(-2.09)	(-0.14)	(5.86)	(4.44)	(4.13)
Log(Floor Number)	-	-	0.0288	0.0395	0.0022	0.0288	0.0391	0.0069
	-	-	(2.72)	(3.27)	(0.15)	(4.21)	(5.02)	(0.48)
Headquarters	-	-	0.0319	0.0306	0.0156	-0.0183	-0.0204	-0.0251
	-	-	(3.41)	(3.20)	(0.79)	(-3.04)	(-3.17)	(-1.37)
Industry NC	-	-	0.2252	0.2670	0.1428	0.1067	0.1240	0.0786
	-	-	(2.76)	(2.87)	(0.93)	(1.75)	(1.22)	(0.79)
Agriculture	-	-	0.0172	-0.0020	0.1006	0.0370	0.0137	0.0591
	-	-	(0.41)	(-0.05)	(1.08)	(1.00)	(0.32)	(0.55)
Mining	-	-	0.1850	0.0356	0.2950	0.0075	-0.0522	-0.0090
	-	-	(2.92)	(0.38)	(2.31)	(0.16)	(-0.61)	(-0.20)
Construction	-	-	-0.0713	-0.0773	-0.0504	0.0145	0.0221	-0.0297
	-	-	(-3.03)	(-2.96)	(-1.39)	(0.89)	(1.12)	(-0.68)
Transport & Utilities	-	-	0.0379	0.0313	0.0450	-0.0125	-0.0042	-0.0811
	-	-	(1.41)	(0.98)	(1.37)	(-0.73)	(-0.19)	(-2.15)
Wholesale	-	-	-0.0466	-0.0507	-0.0327	-0.0194	-0.0242	-0.0277
	-	-	(-2.52)	(-2.32)	(-1.16)	(-1.47)	(-1.54)	(-0.81)
Retail	-	-	0.2268	0.2278	0.2183	0.0862	0.0861	0.0752
	-	-	(8.65)	(7.83)	(6.51)	(5.04)	(4.37)	(1.69)
FIRE	-	-	0.1665	0.1678	0.1625	0.0043	0.0008	-0.0072
	-	-	(7.52)	(7.28)	(4.72)	(0.37)	(0.06)	(-0.23)
Service	-	-	0.1066	0.1073	0.1142	-0.0052	-0.0113	-0.0223
	-	-	(6.10)	(5.60)	(4.06)	(-0.49)	(-0.91)	(-0.77)
Government	-	-	0.1977	0.2123	0.2020	0.0169	0.0101	0.1549
	-	-	(3.36)	(3.53)	(2.42)	(0.60)	(0.32)	(1.57)
Observations	139,757	62,571	62,571	48,099	14,472	62,571	48,099	14,472
R-squared	0.190	0.217	0.072	0.065	0.094	0.024	0.023	0.039
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. Observations for which Risk is NA are omitted.

Table 7: Term Structure (Log Lease Rate/sqft) – Stratified by Age of Establishment

	(1) Age = 1 Zipcode FE	(2) Age 2-5 Zipcode FE	(3) Age 6-10 Zipcode FE	(4) Age > 10 Zipcode FE	(5) Age = 1 Bldng FE	(6) Age 2-5 Bldng FE	(7) Age 6-10 Bldng FE	(8) Age > 10 Bldng FE
Risk_Low	0.1400	0.0330	0.0821	0.1450	0.2120	-0.0602	0.0918	0.0889
	(1.89)	(0.40)	(1.04)	(1.74)	(2.10)	(-0.74)	(1.10)	(1.49)
Log(lease length)	0.2731	0.1471	0.1039	0.0858	0.1657	0.0595	0.0483	0.0187
	(16.25)	(7.56)	(5.17)	(3.98)	(6.77)	(3.17)	(2.38)	(1.37)
Risk_Low*Log(LL)	-0.0455	-0.0128	-0.0167	-0.0358	-0.0590	0.0147	-0.0215	-0.0194
	(-2.45)	(-0.57)	(-0.85)	(-1.71)	(-2.35)	(0.71)	(-1.03)	(-1.35)
Log(Age Estab)	-	-	-	-0.0051	-	-	-	0.0131
	-	-	-	(-0.51)	-	-	-	(2.16)
Log (Leased space)	-0.1262	-0.0672	-0.0684	-0.0375	-0.0556	-0.0168	-0.0408	-0.0166
	(-9.89)	(-4.97)	(-6.85)	(-4.07)	(-5.18)	(-1.50)	(-3.84)	(-3.37)
Log (wrkrs/sqft)	-0.0006	-0.0216	-0.0134	0.0096	-0.0003	-0.0195	-0.0314	-0.0066
	(-0.08)	(-2.81)	(-2.30)	(2.28)	(-0.05)	(-3.06)	(-5.73)	(-2.21)
Ground Level	0.0072	-0.0185	-0.0741	-0.0676	0.1196	0.0345	0.0388	0.0502
	(0.17)	(-0.54)	(-2.66)	(-3.12)	(3.38)	(1.32)	(1.56)	(3.51)
Log(Floor Number)	0.0047	0.0373	0.0323	0.0468	-0.0092	0.0365	0.0381	0.0451
	(0.30)	(2.10)	(2.11)	(4.31)	(-0.50)	(2.40)	(2.43)	(4.95)
Headquarters	-0.0247	-0.0599	-0.0109	0.0576	-0.0805	-0.0752	-0.0565	0.0057
	(-0.88)	(-2.84)	(-0.66)	(6.06)	(-2.29)	(-3.24)	(-3.33)	(0.78)
Industry NC	0.2044	0.2838	0.5534	-	0.0712	0.0898	0.3905	-
	(1.57)	(3.59)	(8.98)	-	(0.45)	(1.40)	(2.40)	-
Agriculture	-0.0148	-0.0324	0.0844	0.0838	0.0654	0.0877	-0.0627	0.0601
	(-0.21)	(-0.25)	(0.93)	(1.71)	(0.72)	(0.52)	(-0.52)	(1.13)
Mining	0.2930	0.4407	0.0464	0.1820	0.0261	-0.0286	0.0967	0.0053
	(1.15)	(1.98)	(0.75)	(1.79)	(0.30)	(-0.37)	(1.43)	(0.04)
Construction	-0.1141	-0.0642	-0.0802	-0.0412	0.0884	-0.0664	-0.0293	0.0091
	(-2.85)	(-1.55)	(-1.56)	(-1.56)	(1.56)	(-1.33)	(-0.43)	(0.35)
Transport & Utilities	0.0012	0.0535	0.1026	0.0090	0.0106	-0.0054	0.0374	-0.0053
	(0.03)	(1.23)	(2.31)	(0.27)	(0.21)	(-0.10)	(0.85)	(-0.17)
Wholesale	-0.0597	-0.0526	-0.0360	-0.0399	0.0356	-0.0710	0.0194	-0.0108
	(-1.85)	(-1.52)	(-1.16)	(-2.06)	(0.77)	(-1.73)	(0.51)	(-0.54)
Retail	0.2572	0.2012	0.1327	0.1689	0.1786	-0.0274	0.0971	0.0506
	(6.53)	(4.30)	(2.82)	(5.63)	(3.54)	(-0.61)	(2.13)	(1.85)
FIRE	0.1409	0.1234	0.1582	0.1998	0.0420	-0.0661	-0.0147	0.0180
	(3.18)	(3.75)	(4.67)	(8.36)	(1.07)	(-2.07)	(-0.53)	(0.99)
Service	0.0739	0.0888	0.0994	0.1298	0.0116	-0.0434	-0.0271	-0.0009
	(2.45)	(3.12)	(3.35)	(6.35)	(0.32)	(-1.47)	(-1.08)	(-0.05)
Government	0.1772	0.0308	0.1196	0.2421	0.0882	-0.2079	0.0162	0.0016
	(3.59)	(0.28)	(1.74)	(2.99)	(1.38)	(-1.66)	(0.17)	(0.04)
Observations	11,711	10,682	11,239	28,939	11,711	10,682	11,239	28,939
R-squared	0.171	0.071	0.061	0.058	0.079	0.039	0.039	0.010
Age FE	-	3	5	-	-	3	5	-
Zipcode FE	1,074	978	976	1,221	-	-	-	-
Building FE	-	-	-	-	6,907	6,129	6,071	10,261

[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. 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 $\partial r^g/\partial k^b < 1$.