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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.

JEL-Codes: R300, M200.

Keywords: lease length, tenant riskiness, rent term structure.

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

by

Jan K. Brueckner and Stuart S Rosenthal*

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. With default risk likely to militate against long-term leases, 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 several concrete risk measures. The first is a firm-level risk variable computed by Dun & Bradstreet based on their observations of individual firms, which is merged with our lease data. A second measure captures the age of the establishment. Our empirical model also includes other controls, including the tenant's SIC industry code, which may capture risk elements as well as the need for relation-specific investments (as in the restaurant industry) that favor long leases.

While the conceptual connection between risk and contract length seems intuitive, we seek stronger grounds for our hypothesis by developing a theoretical model that explores this

[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.

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 contract length.[2] 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).[3]

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. If both contract terms are offered, landlords must be indifferent between them, a requirement that pins down the rent level under the LT contract. A key feature of the model is that a tenant may default in period 1 under the LT contract, which occurs when the tenant's revenue falls short of the LT rent level.

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, and landlords should earn the same expected profit on the contracts, conditional on the assignment of tenants. We show that, if the period-1 revenues of the tenant types are sufficiently different, then the assignment of bad tenants to ST contracts and good tenants to the LT contract is an equilibrium.

Tenant riskiness is also connected to the term structure of lease contracts, which is the subject of a small literature,[4] and a second purpose of the paper is to study this connection. As in the case of interest rates, lease contracts also have a term structure, with the initial rent on a lease dependent on the length of the contract. Among the sources of this dependence are concerns about future inflation. If short-term rents are expected to rise over time along with the general price level, landlords will require compensation via a higher initial rent when writing a long-term lease,

[2] Harris and Holmstrom (1987) and Poutvaara et al. (2017) propose theoretical lease-length models that apply to other contexts beside commercial leasing. Another empirical focus is on the duration of union labor contracts, as in Gray (1978).

[3] 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).

[4] See Grenadier (1995, 2005) for theory and Gunnelin and Soderberg (2003) and Bond et al. (2008) for empirical evidence.

leading to an “upward-sloping” term structure of rents. While this expected-inflation concern can be addressed 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. 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.

Beyond these inflation-related factors, a third 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, however, 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. 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. 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. This prediction is also tested in the paper.

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.[5] These data were matched at the establishment level with tenant information from Dun & Bradstreet.[6] 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

[5] 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.

[6] Recent papers that use D&B establishment-level data include Liu, Rosenthal and Strange (2022), 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.[7] The Dun & Bradstreet 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. Controlling for that measure, we also find that older companies have longer leases. Establishment age is also a strong indicator of tenant risk given high failure rates among young companies.

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. We run different regressions for tenants in D&B's low-risk category and risky tenants (those in the medium and high-risk categories), finding that the term-structure slope is higher for low-risk tenants, who pay a greater premium for a long-term contract than do risky tenants. The results thus suggest that tenant riskiness is an ingredient into the observed 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, and section 5 offers conclusions.

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

2. A theoretical model

2.1. The setup

In the model, both tenant types are risk neutral and 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 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

Let r_0 and r_1 denote the ST rents in the two periods. In period 0, rent is set equal to tenant revenue p_0, with $r_0 = p_0$ yielding zero profit for both tenant types. In period 1, landlords adjust ST rents to match the fortunes of the two tenant types, so that r_1 depends on the type. Specifically, $r_1^i = p_0 + k^i + \epsilon,\ i = g, b$, where ϵ is the realization of the common random effect. Rents again reduce tenant profit to zero, but they now differ for the two types in period 1. With tenant ST profit thus equal to zero in both periods, the expected present value (EPV) of ST profit across the periods is also zero for both tenant types. In contrast to an alternate model with landlord competition, where rents would be driven down to the landlord's cost level, this approach allows rents to vary with tenant willingness-to-pay in a way that seems realistic.

While the zero-tenant-profit feature of ST contracts means that default is not an issue, default can occur under an LT contract. Let r denote the LT rent, which prevails in both periods. Then, if a type-i tenant is present, period 1 default occurs when revenue is less than r, or $p_0 + k^i + \epsilon < r$. Equivalently, default occurs when $\epsilon < r - p_0 - k^i$. Recognizing the possibility of default, the type-i tenant's EPV of profit under an LT contract is

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

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

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 firm goes out of business, paying no rent and earning no revenue (with period-1 profit thus equal to zero). Renegotiation of rent is ruled out, and the tenant is also assumed to be unable to relocate in period 1 to another property offering an ST contract.

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

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

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 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. 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

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

Note that $r > c$ must hold for (4) to be nonnegative.[8]

[8] 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

2.2. Equilibrium analysis

When r is held fixed, 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

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

noting that the derivative with respect to the lower limit of integration equals zero given the default condition. With the derivative positive, it follows that the good tenant earns a higher present value of LT profit than the bad tenant holding r fixed, reflecting higher period-1 profit in the no-default state, a consequence of $k^g > k^b$. While this result suggests that good tenants will value the LT contract by more than bad tenants (who then 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, 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

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

which determines r as an implicit function of the parameters of the model. 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

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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.

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

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 contract, 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[9]

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

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

[9] It could be argued that the condition (8) should be modified to better reflect the parametric-rent assumption embodied in (9) below. In particular, in switching to the ST contracts, the good tenant may expect to pay rent of $p_0 + k^b + \epsilon$ in period 1, the amount that would be paid by the current bad tenant, not $p_0 + k^g + \epsilon$. Rather than being zero, the good tenant's period-1 profit would then equal $k^g - k^b$, and the EPV of profit after switching from the LT to the ST contracts would equal $\delta(k^g - k^b)$, not zero. Accordingly, the zero on the RHS of (8) would be replaced by $\delta(k^g - k^b)$. However, the original approach of setting the RHS of (8) equal to zero seems more natural. First, the parametric-rent viewpoint is partly captured in the original approach, with the good tenant in period 0 expecting to pay the rent p_0 currently paid by the bad tenant, which also yields zero period-0 profit for the good tenant. Second, since the (uncertain) period-1 ST rent paid by the bad tenant is not known ex ante, when contract types are being chosen, it may not be appropriate to apply the parametric-rent notion to this period, as is done above. It may be more plausible to assume that the good tenant expects the uncertain period-1 rent to reflect his identity, not that of the current bad tenant, if he switches to the ST contracts.

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 is an equilibrium when the tenants' period-1 revenues diverge sufficiently, with k^g and k^b sufficiently large and small, respectively.*

The proposition is established by first showing that (8) holds when k^g is large. Since $\partial r^g/\partial k^g < 0$ holds from above, $r^g - p_0 - k^g$ decreases as k^g rises, eventually falling below $\underline{\epsilon}$. The possibility of rent default by the good tenant then disappears (see the integrals in (3)), allowing π_{LT}^{g} from (1) to be written as[10]

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

using $\Delta\Pi = 0$ from (7), which validates (8). By continuity, (10) will also hold when k^g is large but not large enough to eliminate the possibility of default.[11]

To show that (9) holds when k^b is sufficiently small, observe that the inequalities $0 < \partial r^g/\partial k^b < 1$ from above imply that $r^g - p_0 - k_b$ decreases with k^b, thus eventually rising above $\overline{\epsilon}$ as k^b falls. With default by a bad tenant paying r^g then becoming certain, $\pi_{LT}^{b}(r^g) < 0$ follows, validating (9).[12] 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, the assignment of the good (bad) tenants to LT (ST) contracts is an equilibrium. Landlords earn identical profit

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[10] 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).

[11] 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.

[12] 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.

regardless of which contracts they offer, and 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 additive form for the tenant revenue differential in the future period, the lesson appears to 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.

3. Data and Summary Statistics

3.1. Data

As highlighted earlier, we use an establishment-level matched sample to conduct our analysis. For these purposes, lease data are obtained from CompStak Inc. while establishment attributes are 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.[13]

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

The lease data are proprietary and were drawn from the CompStak database in October 2021. These data originate from commercial real-estate agent files as part of a sharing arrangement

[13] 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.

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, all 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 does 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.[14] 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. This pattern is evident in Panel C of Table 1, which reports summary measures for the lease and establishment attributes in our estimating sample. Observe that for the matched sample, median and mean establishment age in 2018 when the D&B data were downloaded are 12 years and roughly 18.4 years, respectively. In comparison, for the D&B data without matching to CompStak, median and mean age of establishments are 11 years and 15.6 years, respectively, reflecting the tendency for the matched file to be comprised of older companies.[15]

Some of the measures used in our analysis are either time-invariant or largely so, which helps to ensure our focus on attributes at the time a lease was originated. These attributes include establishment industry classification (based on SIC 1 code), whether the establishment is a headquarters, and the risk attribute of the establishment as reported by D&B in 2018. From CompStak, we also observe the amount of space leased, effective rent per square foot, and whether the lease is being issued to a new arrival in the building or whether it is a renewal of an existing tenant lease.

Age of establishment at the time a lease is executed is a strong predictor of tenant risk given the high failure rate of newly established companies. For that reason, in the regressions that follow

[14] 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.

[15] These measures are based on D&B records for which employment is reported.

we condition on establishment age at the time the lease was originated. To do so, we adjust the age of the establishment as reported by Dun and Bradstreet in 2018 for the years between 2018 and lease origination. 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. In the estimation, we then condition on the log of adjusted age as the control measure.

We also control for establishment employment per square foot of space leased. For this measure, 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 change in establishment employment since the lease was executed. For that reason, we experimented with dropping this measure from our estimation and found that results were robust.

As will also become apparent, in many instances leases 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 models.

Our matched record datafile is unique and its existence makes this study possible. The data provide detailed establishment-level information on lease and tenant attributes for establishments spread across a large number of cities.

3.2. Variables

In our primary regressions, the dependent variable is the log of lease length in months. To simplify discussion, the variable name is abbreviated as **Llease_length** in most places in the text, with analogous abbreviations adopted for other variables used in the analysis. More complete variable labels are provided in the tables.

All regressions control for the log of the age of the establishment at the time the lease was executed (a possible risk measure), which is denoted **Lage_estab**, and the square footage of the space being leased, also represented in log form and denoted **Lspace**. An additional control present in all the regressions is **Lwpsqft_estab**, which equals the log of workers per square foot of leased space. It represents a crowding measure, with a high value perhaps indicating long-term inadequacy of the amount of space leased and hence a desire for a short-term contract.

Our most direct indicator of establishment risk is its D&B risk classification. This classification is based on a risk score calculated by D&B for each establishment and indicates the likelihood that a firm will be unable to pay its bills.[16] We use the categorical version of the risk measure reported by D&B, with risk classified as 1-0 dummy variables for low, medium and high risk, **Risk_Low**, **Risk_Med** and **Risk_High**, respectively, where risk assessment is based on the company's score as described earlier. In the regressions, **Risk_High** is the omitted reference variable. We also include a 1-0 dummy, denoted **Risk_NA**, for those instances where the risk measure is missing, which occurs in roughly 21.6% of the matched sample. **Lage_estab**, mentioned above, is also a strong proxy for tenant riskiness, with older companies being less likely to fail and thus less risky as tenants.

An additional control in most regressions is **Headquarters**, a dummy variable indicating that the establishment is a firm's headquarters, potentially leading to a long-term lease. Another control appearing in some regressions is the log of employment density (employment per square mile) for the zip code containing the leased space, denoted **Lempsqft_zipcode**. Because high-density locations may be highly valued, longer leases may emerge.

Additional controls used in most regressions are dummy variables indicating the single-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.

The regressions also include alternate sets of geographic fixed effects. The first set consists of city fixed effects, of which there are 1,045. Other regressions use 5-digit zip-code fixed effects (numbering 1,868), while additional regressions use 38,031 fixed effects for individual buildings. Building fixed effects are especially powerful in controlling for unmeasured locational characteristics that may affect lease length.

We also use information on whether the lease is for a newly arrived tenant in the building as opposed to a being a renewal for an existing tenant, denoted by the dummy variable **NewT**. In many of the specifications, this variable is used to split the sample into subsamples of new and existing tenants. As noted earlier, landlords have less information on newly arrived tenants, and

[16] As noted earlier, the D&B risk measure is based on company type, age, active lawsuits, liens or judgements, company net worth, and trade data. Additional details are at: https://www.dnb.com/resources/financial-stress-score-definition-information.html.

for that reason, we anticipate that they will place more weight on the D&B risk measure than in the case of lease renewals. For the latter, landlords have personal knowledge of the tenant's rent payment history. Stratifying sample by **NewT** effectively interacts lease type with all other controls in the model, including location-specific fixed effects. This approach allows for many other possible differences between new and renewal tenants and helps to ensure reliable estimates of the difference in coefficients on the risk measures when comparing the two sets of lease records.[17]

Finally, in the regressions exploring the term structure of rental contracts, we use the log of effective monthly rent per square foot as the dependent variable, denoted **Lrent**. 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.[18]

Panels C and D of Table 1 provide summary statistics for these measures, as noted above. In all cases, values are based on the common estimating sample used for all of the models that follow. Notice that 60% of tenants are in the low-risk category, with roughly 9% falling in each of the other risk categories. The risk assessment is missing for 22% of the observations.[19] The average lease length is 5-1/2 years (66.6 months) while leased space is roughly 22,310 square feet on average. 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 at the time a lease is executed is older than for the overall population of companies (with a median age of 12.8 years). 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.

[17] 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 account 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.

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

[19] Results are robust when we drop observations for which the risk measure is missing.

4. Empirical results

4.1. Contract-length regressions

Table 2 shows the basic contract-length regression results. The regression in column 1 contains only the risk dummies and the controls for age of establishment (**Lage_estab)**, space leased (**Lspace)**, and workers per square foot within the leased spaced (**Lwpsqft_estab)**, all in logs. Focusing first on these controls, older establishments (which the landlord may view as less risky) receive longer leases, although the coefficient is only marginally significant. Lease length also increases in the amount of space leased, with a statistically significant elasticity of near 0.195. That tenants who occupy substantial floor space receive long leases seems natural, given the high costs of relocation for large tenants. The worker crowding measure **Lwpsqft_estab** has a positive, significant effect on lease length, contrary to expectations. That pattern reverses, however, as additional controls are added to the model in later columns of the table.

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 safer tenants receive longer leases than high-risk tenants, confirming the main hypothesis. The leases of these lower-risk tenants are from 4.4% to 5% longer than those of the riskiest tenants. A missing risk measure is associated with shorter leases, as seen in the significantly negative coefficient of **Risk_NA**, suggesting that risk information used by D&B tends to be missing for high-risk tenants. Note finally that, while the explanatory power of the regression is modest, the R^2 value of 0.161 nevertheless indicates that the simple set of controls in column 1 have notable predictive power.

Column 2 of the table adds the SIC dummies and the headquarters variable. These additions have little effect on previous coefficients except for the age measure, whose coefficients doubles in magnitude and becomes significant. The headquarters effect is significantly positive, as expected, and the SIC dummies 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 highlighted in the table.

Column 3 adds zip code employment density, which has a positive effect on lease length, perhaps indicating that tenants value dense locations and want ongoing exposure to their benefits. 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 overall the change is modest (the crowding coefficient becomes insignificant). Of the measures of primary interest, the **Risk_Med** coefficient becomes notably smaller and insignificant, but the **Risk_Low** coefficient close to that in column 2.

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 FEs are added in column 4, the **Risk_Low** coefficient becomes 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).

Column 5 shows the effects of adding zip-code FEs while dropping the zip-code employment-density variable, and the results are mostly similar to those in column 4. Column 6 shows the effect of adding 38,031 fixed effects for individual buildings, the narrowest geographic control. The **Risk_Low** coefficient remains significant and close in size to its values under city and zip code fixed effects. In contrast to the results in columns 1-3, which showed a 3.5-4.5% increase in lease length, columns 4-6 indicate that the leases of low-risk tenants are 2.9% longer than those of high-risk tenants (the omitted category). The effect of establishment age regains significance in column 6, being larger than the values in columns 1-3. Also, in column 6, the **Lwpsqft_estab** coefficient becomes negative and significant (in contrast to the previous positive values), indicating that establishments signing leases for crowded space choose shorter contracts, as conjectured. In addition, the coefficients for the Retail, FIRE and Service SIC codes remain significant but are notably smaller than in previous columns.

Since 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 observations, Table 3 divides the sample into "New Arrival" and "Renewal" subsamples, running the zip-code and building-fixed-effect regressions on the two subsamples. 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 lease renewals, the **Risk_Low** coefficient is much smaller and insignificant along with that of **Risk_Med**, showing that among existing tenants, the risk measures are irrelevant in determining lease length. 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.[20] 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 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 3, 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 lease renewals. Therefore, with even finer geographic controls, the risk measures are again only relevant for new tenants.

Tables 4 and 5 present robustness checks. Again splitting the sample between new tenants and lease renewals, Table 4 divides it further into two tenant groups: export-oriented tenants and tenants serving the local market. The export-oriented group consists of tenants in the mining, construction, transportation/utility, wholesale and manufacturing sectors, with manufacturing the omitted category, while the locally oriented group consists of tenants in Retail, FIRE, and Service, with Service as the default. For tenants serving the local market, the risk-coefficient patterns are the same as in Table 3, with the **Risk_Low** coefficient significant for new tenants and insignificant for renewals. But for export-oriented tenants, the **Risk_Low** coefficients are insignificant for both new and renewal tenants. This subsample, however, represents a small share of the overall sample, containing less than one-fifth of the observations in the locally oriented subsample, and this sharply reduced sample size reduces the precision of the estimates. It is worth noting nevertheless that the magnitudes of the **Risk_Low** coefficients are roughly similar to those seen in earlier models.

[20] 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.

Table 5 returns to the full sample while including only leases in the biggest cities: New York, Chicago, and Los Angeles, distinguishing again between new tenants and renewals. As can be seen, the sample sizes for the new and renewal subsamples are cut by about half under this big-city restriction. The table shows exactly the same risk coefficient pattern as before, with the **Risk_Low** coefficient significantly positive for new tenants and insignificant for lease renewals. Thus, even in the largest cities, the risk measures are relevant only for new tenants. The effects of the main controls are similar to those in Table 3. As for the SIC coefficients, the Retail coefficient, which was strongly positive and significant in Tables 1 and 2, remains so in the three largest cities regardless of lease type (new or renewal) and the choice of fixed effects. Overall, Tables 4 and 5 mostly confirm the previous findings on risk effects, showing that the D&B risk variables are relevant only for new tenants, with concerns about the riskiness of tenants who are renewing their leases tenants allayed by prior experience.

4.2. Term-structure regressions

We now turn to an exploration of the effects of tenant riskiness on the term structure of rents. Since the landlord needs to be compensated for possible tenant misbehavior, the scope for which is greater with a long-term lease, the rent premium for such a lease should be greater when the contract involves a high-risk tenant as compared to a low-risk tenant. To test this hypothesis, we divide the sample into two subsamples, one containing low-risk tenants and the other containing medium- and high-risk tenants (referred to as risky), using the D&B risk measures. Within these subsamples, we compare the effects of lease length (treated as exogenous) on rent, expecting a smaller effect (a flatter term structure) for low-risk tenants.[21] While this sample division is different from the new-tenant/renewal-tenant division used in the lease-length analysis, these groups are reintroduced later as subcategories with the low-risk/risky categories.

[21] Our approach follows earlier papers on the rental term structure, where lease length is treated as exogenous and thus uncorrelated with the regression error term. The presence of omitted variables, however, can create such correlation, leading to biased estimates. The error term could include unmeasured aspects of the quality of leased space, which would affect rent in a positive direction. If unobserved space quality is positively correlated with lease length, as seems likely, then the result is an upward-biased estimate of the lease-length coefficient in the rent regression. Moreover, if this correlation is larger for low-risk tenants than for risky tenants, as also seems likely, then the upward term-structure bias would be larger for low-risk tenants, tending to make the term structure steeper for these tenants than for risky tenants. As a result, our key finding below that the reverse relationship holds (a steeper term structure for risky tenants) is unlikely to be due to omitted variable bias. This conclusion, of course, rests on the accuracy of the previous correlation scenario.

In the regressions, the dependent variable is **Lrent**, the log of effective (initial) rent per square foot. The key independent variable is the log of lease length, **Llease_mt**, which was the dependent variable in the previous regressions. As before, additional controls are included for the amount of space leased, tenant age, crowding, and additional controls to capture the quality of space ("suite" attributes).[22] The coefficients for the full set of controls are reported in Table B-2 in the appendix.

The main results are presented in Table 6. Not present in this table is an initial regression of **Lrent** on **Llease_mt** that uses the full sample (containing both risky and low-risk tenants). While this regression generates a positive lease-length coefficient, indicating an upward-sloping rental term structure in a pooled sample, columns 1 and 2 of Table 6 show separate regressions for the low-risk and risky subsamples.[23] These regressions, which omit location fixed effects but control for zip-code employment density, show positive term structures for both risk groups. However, the effect of lease length on rent is larger for risky tenants than for low-risk tenants, validating our hypothesis. A 10% increase in lease length raises rent by 1.7% for risky tenants, while rent rises 1.2% for low-risk tenants. Establishment age, which may also capture tenant riskiness, is omitted from these two regressions along with other establishment and suite attributes. But columns 3 and 4 show that the term-structure difference persists when age and other establishment and suite attributes are taken into account. Now, a 10% increase in lease length raises rent by 2.6% and 1.6% for risky and low-risk tenants, respectively.

Columns 5 and 6 show regressions that include zip-code fixed effects, with the zip-code employment-density control dropped. The previous qualitative pattern remains, with a longer lease raising rent by more for risky tenants than for low-risk tenants.

The lease-length regressions in section 4.1 showed that tenant riskiness as measured by D&B only mattered for new tenants. To see whether the same pattern emerges in the term-structure case, columns 7-10 of Table 6 show the effect of tenant riskiness on term structure separately for new and renewal tenants. Columns 7 and 8 show that riskiness continues to steepen the term structure when attention is restricted to new tenants. But columns 8 and 9 show that this same

[22] These latter measures include **Ground floor**, a dummy variable indicating that the space is on the second or lower floor of the building, and **Log (floor + 1)**, 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).

[23] The coefficient on log lease length in the pooled sample regression using the same specification as in columns 1 and 2 is 0.132 (with a t-ratio of 10.61). The estimate thus lies between the estimates in columns 1 and 2, as anticipated.

conclusion applies when attention is restricted to renewal tenants. Therefore, regardless of whether a lease is new or a renewal, the effect of lease length on rent is larger for risky tenants. Thus, risky tenants face a steeper term structure regardless of whether they are new tenants or are renewing a lease.[24]

This conclusion contrasts with the effect of the D&B risk measures in the determination of lease length, where the measures only mattered for new tenants. Evidently, the D&B measures provide additional information to the landlord that is useful in setting rents on long-term contracts even when the tenant is renewing a lease and is thus a known entity.

The novel insight yielded by these findings is that tenant riskiness appears to play a role in generating the observed term structure of commercial leases. One implication is that, if all tenants were to have low risk, the term structure would be flatter than the (pooled) one that previous researchers have studied.

5. 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 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, 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, appears to serve as a risk proxy for both new and existing tenants, with older establishments getting 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 potential 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 premium than the one that compensates just for inflation risk when renting

[24] This same result appears to hold when we replace the zip code fixed effects with building fixed effects. However, stratifying the sample as in columns 6-10 results in relatively few observations per building, and results are not reported for that reason.

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 lower-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	

Panel C: Lease/Estab Attributes	Obs	Mean	10th Pctl	50th Pctl	90th Pctl
Lease length (months)	127,872	66.65	24	60	120
Net effective rent/sq. foot ($2018)	127,872	37.83	9.72	29.27	69.08
Newly arrived tenant lease	127,872	0.57	0	1	1
Age of estab in 2018 (yrs)	127,872	18.42	3	12	39
Age of estab at lease execution (yrs)	127,872	12.85	0	6	33
Risk assessment – Low	127,872	0.604	0	1	1
Risk assessment – Medium	127,872	0.091	0	0	0
Risk assessment – High	127,872	0.089	0	0	0
Risk measure missing	127,872	0.216	0	0	1
Leased space (1,000 square feet)	127,872	22.31	1.20	5.04	42.50
Emp/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/Square mile land area in Zipcode	127,872	96,561	1,155	7,510	331,005

Panel D: 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: Lease Length – Core Estimates[a]

	(1) Risk+Space	(2) Estab Atrib	(3) Density	(4) City FE	(5) Zip code FE	(6) Building FE
Log (Emp/sqft zipcode)	-	-	0.0591	0.0027	-	-
	-	-	(11.92)	(0.26)	-	-
Risk_Low	0.0443	0.0396	0.0340	0.0299	0.0288	0.0287
	(4.55)	(4.27)	(3.78)	(2.29)	(3.57)	(3.29)
Risk_Med	0.0497	0.0348	0.0151	0.0038	0.0022	-0.0161
	(3.65)	(2.75)	(1.19)	(0.19)	(0.17)	(-1.41)
Risk_NA	-0.0417	-0.0440	-0.0631	-0.0620	-0.0604	-0.0582
	(-3.76)	(-4.13)	(-6.22)	(-7.11)	(-6.77)	(-5.76)
Log (Age estab)	0.0067	0.0117	0.0071	-0.0008	-0.0001	0.0144
	(1.70)	(3.21)	(2.05)	(-0.23)	(-0.04)	(6.95)
Log (Leased space sqft)	0.1951	0.2059	0.1850	0.1929	0.1992	0.2077
	(33.35)	(43.30)	(44.68)	(39.54)	(53.28)	(54.26)
Log (Wrkrs/sqft leased)	0.0086	0.0082	0.0022	0.0019	0.0007	-0.0059
	(2.41)	(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	127,871	127,871	127,872	127,872
R-squared	0.161	0.194	0.226	0.168	0.170	0.124
Zip code FE	-	-	-	-	-	38,031
Building FE	-	-	-	-	1,868	-
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: 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 4: Lease Length By Industry Grouping[a]

	Agriculture, Mining, Construction, Transport, Wholesale (Omitted Industry: Manufacturing)				Retail, FIRE (Omitted Industry: Service)			
	(1) New Arrival Lease Zip code FE	(2) Renewal Lease Zip code FE	(3) New Arrival Lease Bldg FE	(4) Renewal Lease Bldg FE	(5) New Arrival Lease Zip code FE	(6) Renewal Lease Zip code FE	(7) New Arrival Lease Bldg FE	(8) Renewal Lease Bldg FE
Risk Low	0.0279	-0.0352	0.0466	-0.0345	0.0416	0.0174	0.0322	0.0270
	(1.56)	(-1.34)	(1.27)	(-0.61)	(3.51)	(1.22)	(2.46)	(1.43)
Risk_Med	0.0307	-0.0665	0.1012	-0.0430	0.0087	-0.0099	-0.0290	-0.0159
	(1.24)	(-1.37)	(1.99)	(-0.50)	(0.52)	(-0.50)	(-1.74)	(-0.62)
Risk_NA	-0.0552	-0.1181	-0.0290	-0.0642	-0.0854	-0.0342	-0.0668	-0.0536
	(-2.54)	(-3.09)	(-0.73)	(-0.84)	(-6.64)	(-2.02)	(-4.72)	(-2.19)
Log (Age estab)	0.0325	0.0468	0.0543	0.0347	0.0247	0.0541	0.0471	0.0558
	(5.74)	(3.15)	(5.01)	(1.04)	(7.44)	(10.35)	(17.39)	(9.67)
Log (Leased space sqft)	0.1887	0.1606	0.1942	0.1689	0.2085	0.1883	0.2144	0.1985
	(21.57)	(12.37)	(10.53)	(6.41)	(46.36)	(35.11)	(46.88)	(29.73)
Log (Wrkrs/sqft leased)	-0.0118	-0.0208	-0.0142	0.0187	0.0056	-0.0033	-0.0098	-0.0024
	(-1.93)	(-2.22)	(-1.22)	(1.09)	(1.75)	(-0.97)	(-3.25)	(-0.53)
Headquarters	-0.0087	0.0402	-0.0133	0.0508	-0.0086	0.0033	-0.0023	0.0069
	(-0.42)	(1.44)	(-0.33)	(0.87)	(-0.74)	(0.29)	(-0.22)	(0.52)
Agriculture	0.1385	0.1793	0.0535	0.1361	-	-	-	-
	(3.40)	(2.81)	(0.55)	(1.14)	-	-	-	-
Mining	-0.0064	0.3423	-0.1083	0.3315	-	-	-	-
	(-0.07)	(1.52)	(-0.77)	(1.43)	-	-	-	-
Construction	-0.0308	0.0081	-0.0117	0.0049	-	-	-	-
	(-1.79)	(0.34)	(-0.32)	(0.09)	-	-	-	-
Transport & Utilities	-0.0398	-0.0401	-0.0531	0.0008	-	-	-	-
	(-2.56)	(-1.51)	(-1.76)	(0.02)	-	-	-	-
Retail	-	-	-	-	0.2217	0.1522	0.1235	0.0987
	-	-	-	-	(17.30)	(9.04)	(8.95)	(4.23)
FIRE	-	-	-	-	-0.0085	-0.0086	-0.0120	-0.0200
	-	-	-	-	(-0.91)	(-0.55)	(-1.43)	(-1.52)
Observations	10,136	7,470	10,136	7,470	54,895	42,455	54,895	42,455
R-squared	0.181	0.137	0.115	0.056	0.206	0.149	0.178	0.115
Zip code FE	1,046	1,030	-	-	1,595	1,627	-	-
Building FE	-	-	7,412	4,888	-	-	20,837	15,422

[a] t-ratios in parentheses based on robust standard errors clustered at the level of the fixed effects (zip code or building). Data are from the establishment-level matched CompStak and Dun and Bradstreet establishment level sample.

Table 5: Lease Length in New York, Los Angeles, and Chicago[a]

	(1)	(2)	(3)	(4)
	New Arrival Lease Zip code FE	Renewal Lease Zip code FE	New Arrival Lease Bldg FE	Renewal Lease Bldg FE
Risk_Low	0.0346	0.0041	0.0447	0.0152
	(2.46)	(0.24)	(2.84)	(0.65)
Risk_Med	-0.0029	-0.0064	-0.0099	0.0003
	(-0.15)	(-0.25)	(-0.49)	(0.01)
Risk_NA	-0.0530	-0.0280	-0.0381	-0.0489
	(-3.25)	(-1.19)	(-2.14)	(-1.49)
Log (Age estab)	0.0245	0.0462	0.0418	0.0423
	(5.90)	(5.73)	(11.86)	(4.81)
Log (Leased space sqft)	0.1975	0.1820	0.2218	0.2099
	(31.40)	(22.85)	(37.20)	(22.42)
Log (Wrkrs/sqft leased)	0.0052	-0.0037	-0.0058	0.0022
	(1.29)	(-0.82)	(-1.45)	(0.37)
Headquarters	0.0210	0.0347	0.0059	0.0197
	(1.94)	(2.17)	(0.44)	(1.10)
Industry NC	0.1253	0.1527	0.0649	0.0394
	(2.81)	(1.95)	(1.55)	(0.37)
Agriculture	0.0253	0.1784	-0.0390	0.0910
	(0.30)	(2.38)	(-0.30)	(0.74)
Mining	0.0590	0.5017	-0.0842	0.2059
	(0.45)	(2.15)	(-0.68)	(1.04)
Construction	-0.0192	-0.0277	-0.0323	-0.0171
	(-0.74)	(-0.75)	(-0.93)	(-0.31)
Transport & Utilities	-0.0232	-0.0660	-0.0576	-0.0554
	(-1.07)	(-1.52)	(-1.90)	(-1.08)
Wholesale	0.0052	-0.0407	-0.0068	-0.0296
	(0.28)	(-1.51)	(-0.26)	(-0.73)
Retail	0.2903	0.2345	0.1264	0.1122
	(14.31)	(8.21)	(4.91)	(2.72)
FIRE	0.0437	0.0395	-0.0167	-0.0321
	(2.39)	(1.20)	(-0.77)	(-0.96)
Service	0.0828	0.0932	0.0085	0.0362
	(5.23)	(3.91)	(0.43)	(1.19)
Government	0.1067	0.2142	0.0237	0.0584
	(0.88)	(2.03)	(0.17)	(0.49)
Observations	31,132	22,682	31,132	22,682
R-squared	0.208	0.171	0.188	0.127
Zip code FE	590	598	-	-
Building FE	-	-	10,684	7,653

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Risk Level	Low	Med+High	Low	Med+High	Low	Med+High	Low	Med+High	Low	Med+High
All, New, or Renewal Leases	All	All	All	All	All	All	New	New	Renewal	Renewal
Log (Emp/sqft zipcode)	0.1299	0.1535	0.1225	0.1761	-	-	-	-	-	-
	(5.52)	(6.23)	(5.40)	(6.68)	-	-	-	-	-	-
Log Lease length	0.1193	0.1704	0.1550	0.2624	0.0979	0.1664	0.0616	0.1043	0.1957	0.2416
	(9.53)	(11.43)	(9.16)	(10.03)	(11.14)	(10.37)	(6.92)	(6.42)	(17.64)	(13.95)
Log (Age estab)	-	-	-0.0335	-0.0297	0.0104	0.0174	-0.0068	0.0017	-0.0167	-0.0104
	-	-	(-4.71)	(-3.03)	(3.24)	(2.56)	(-1.17)	(0.14)	(-4.38)	(-1.46)
Estab and Suite Attributes[b]	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip code Fixed Effects	No	No	No	No	1,436	1,105	1,242	843	1,158	899
Observations	109,417	30,340	48,099	14,472	48,099	14,472	24,053	5,642	24,046	8,830
R-squared	0.180	0.222	0.309	0.369	0.065	0.094	0.051	0.061	0.099	0.135

[a] t-ratios based on robust standard errors clustered by zip-code fixed effects in columns 5-10. Omitted industry category is manufacturing.

[b] Additional controls include: log of space leased, log of workers per square foot within the space leased, a 1-0 dummy for a second-floor or lower level suite, log of floor number (plus 1 to avoid zeros), a 1-0 dummy for headquarter status of the establishment, 1-digit SIC industry classification.

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

Appendix B: Supplemental Tables

Table B-1: Average Values for New and Renewal Lease Records[a]

Panel A: Lease Location (percent)	New Arrival Lease (72,283 Obs)	Renewal Lease (55,589 Obs)
Boston MSA	6.53	7.66
California Major Cities	63.64	58.75
Chicago	6.79	7.69
Washington DC	4.65	4.28
Northern New Jersey	2.21	3.69
New York City	14.82	14.30
Philadelphia	1.37	3.63
Panel B: Lease/Estab Attributes		
Lease length (months)	69.70	62.67
Net effective rent/sq. foot ($2018)	36.55	39.50
Newly arrived tenant lease	1.0	0.0
Age of estab in 2018 (yrs)	15.39	22.37
Age of estab at lease execution (yrs)	8.59	18.38
Risk assessment – Low	0.535	0.694
Risk assessment – Medium	0.106	0.070
Risk assessment – High	0.088	0.092
Risk measure missing	0.271	0.144
Leased space (1,000 square feet)	21.37	23.54
Estab Emp/Leased Space (1,000 sq ft)	3.39	5.80
Headquarters	0.127	0.209
Emp/Square mile in Zipcode	98,195	94,435
Panel C: Industry		
Not classified	0.017	0.005
Agricultural	0.005	0.004
Mining	0.006	0.007
Construction	0.026	0.024
Manufacturing	0.080	0.093
Transport/Utilities	0.044	0.038
Wholesale	0.066	0.067
Retail	0.114	0.089
FIRE	0.143	0.135
Service	0.503	0.540
Government	0.004	0.004

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

Table B-2: Term Structure (Log Lease Rate/sqft)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Risk Level	Low	Med+High	Low	Med+High	Low	Med+High	Low	Med+High	Low	Med+High
All, New, or Renewal Leases	All	All	All	All	All	All	New	New	Renewal	Renewal
Log (Emp/sqft zipcode)	0.1299	0.1535	0.1225	0.1761	-	-	-	-	-	-
	(5.52)	(6.23)	(5.40)	(6.68)	-	-	-	-	-	-
Log Lease length	0.1193	0.1704	0.1550	0.2624	0.0979	0.1664	0.0616	0.1957	0.1043	0.2416
	(9.53)	(11.43)	(9.16)	(10.03)	(11.14)	(10.37)	(6.92)	(17.64)	(6.42)	(13.95)
Log (Age estab)	-	-	-0.0335	-0.0297	0.0104	0.0174	-0.0068	-0.0167	0.0017	-0.0104
	-	-	(-4.71)	(-3.03)	(3.24)	(2.56)	(-1.17)	(-4.38)	(0.14)	(-1.46)
Log (Leased space sqft)	-	-	-0.1089	-0.1522	-0.0555	-0.1003	-0.0374	-0.0753	-0.0736	-0.1212
	-	-	(-7.60)	(-7.55)	(-6.26)	(-8.65)	(-4.07)	(-7.79)	(-5.14)	(-9.87)
Log (Wrkrs/sqft leased)	-	-	0.0268	0.0085	0.0069	-0.0094	0.0047	0.0094	-0.0108	-0.0104
	-	-	(3.19)	(0.93)	(1.71)	(-1.42)	(1.06)	(1.96)	(-1.14)	(-1.44)
Ground floor	-	-	-0.2252	-0.2768	-0.0447	-0.0070	-0.0588	-0.0307	-0.0016	0.0151
	-	-	(-4.15)	(-3.19)	(-2.09)	(-0.14)	(-2.74)	(-1.21)	(-0.03)	(0.28)
Log (floor + 1)	-	-	-0.0725	-0.1898	0.0395	0.0022	0.0341	0.0387	0.0118	0.0140
	-	-	(-1.80)	(-3.21)	(3.27)	(0.15)	(2.05)	(3.78)	(0.61)	(0.74)
Headquarters	-	-	0.1132	0.1652	0.0306	0.0156	0.0284	0.0397	0.0312	-0.0004
	-	-	(5.22)	(3.86)	(3.20)	(0.79)	(2.43)	(3.51)	(1.29)	(-0.02)
Industry NC	-	-	0.3499	0.1861	0.2670	0.1428	0.2956	0.2649	0.3955	0.1225
	-	-	(1.79)	(1.05)	(2.87)	(0.93)	(2.73)	(2.87)	(3.94)	(0.70)
Agriculture	-	-	0.1234	0.2080	-0.0020	0.1006	0.0228	0.0180	-0.1451	0.2701
	-	-	(1.92)	(2.14)	(-0.05)	(1.08)	(0.42)	(0.33)	(-0.83)	(2.34)
Mining	-	-	0.0035	0.7261	0.0356	0.2950	-0.0722	0.0973	0.1421	0.4449
	-	-	(0.02)	(4.63)	(0.38)	(2.31)	(-0.44)	(0.77)	(1.58)	(2.16)
Construction	-	-	-0.1498	-0.1240	-0.0773	-0.0504	-0.0923	-0.0416	-0.0460	-0.0487
	-	-	(-3.44)	(-2.44)	(-2.96)	(-1.39)	(-2.75)	(-1.45)	(-0.87)	(-1.05)
Transport & Utilities	-	-	-0.0142	0.0170	0.0313	0.0450	0.0321	0.0307	-0.0213	0.0390
	-	-	(-0.31)	(0.23)	(0.98)	(1.37)	(0.80)	(1.00)	(-0.46)	(1.09)
Wholesale	-	-	-0.1619	-0.0964	-0.0507	-0.0327	-0.0556	-0.0487	-0.0203	-0.0371
	-	-	(-4.59)	(-2.11)	(-2.32)	(-1.16)	(-2.15)	(-2.21)	(-0.46)	(-1.16)
Retail	-	-	0.3112	0.3078	0.2278	0.2183	0.1752	0.2307	0.1701	0.2285
	-	-	(7.03)	(6.93)	(7.83)	(6.51)	(5.25)	(7.18)	(3.52)	(5.81)
FIRE	-	-	0.3602	0.3280	0.1678	0.1625	0.1644	0.1625	0.1372	0.1632
	-	-	(7.78)	(6.20)	(7.28)	(4.72)	(5.95)	(5.94)	(2.64)	(4.27)
Service	-	-	0.2221	0.2290	0.1073	0.1142	0.1126	0.0922	0.0940	0.1205
	-	-	(6.96)	(4.68)	(5.60)	(4.06)	(4.79)	(4.49)	(2.24)	(3.92)
Government	-	-	0.3124	0.1342	0.2123	0.2020	0.2542	0.1415	0.0221	0.3359
	-	-	(2.89)	(0.83)	(3.53)	(2.42)	(3.21)	(3.95)	(0.14)	(3.28)
Observations	109,417	30,340	48,099	14,472	48,099	14,472	24,053	24,046	5,642	8,830
R-squared	0.180	0.222	0.309	0.369	0.065	0.094	0.051	0.099	0.061	0.135
Zip code FE	-	-	-	-	1,436	1,105	1,242	1,158	843	899

[a] T-ratios based on robust standard errors clustered at the the fixed effects in columns 3-6 (zip code or building). Omitted industry category is manufacturing.