Space Market Matching as Jigsaw Puzzle Games: the Abundance Premium*

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Abstract

The matching between tenants and landlords in the space market is like jigsaw puzzle games: landlords compete for leases with different sizes and terms to fill their buildings. We hypothesize that landlords value a lease less if there are more similar leases in the market, so the tenant of the lease needs to pay higher rents. We call this the Abundance Premium. Leveraging a newly available dataset, we use 60,730 class A office leases in the largest five markets in the U.S. from 2010 to 2019 to propose and calculate an Abundance measure for each lease. We find strong evidence that lease Abundance significantly increases rents: when the Abundance increases by 100 basis points, the rent increases by \$0.03 per square foot per month, holding constant other factors. This finding is robust across regions and the sample period. We also find that the Abundance Premium is stronger for leases with larger sizes and in larger buildings.

Keywords: Commercial Real Estate, Space Market, Searching and Matching, Market Segmentation, Lease Abundance

JEL classification: C4, G1, M2, R3

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1. Introduction

Space is an important factor in economic production and one of the most valuable assets in the U.S. The total value of U.S. homes was more than $45 trillion at the end of 2022,[3] and the total value of commercial real estate was more than 20 trillion dollars at the end of 2021.[4] Space markets, those of both residential and commercial, are well known for being segmented. The literature has much evidence of the segmentation of the housing market (see, e.g., Straszheim (1975), Goodman (1978), Dale-Johnson (1982), Goodman and Dubin (1990), Maclennan and Tu (1996), Goodman and Thibodeau (1998), Bourassa, Hamelink, Hoesli and MacGregor (1999), Orford (2000), Watkins (2001), Orford (2002), Bourassa, Hoesli and Peng (2003), Goodman and Thibodeau (2003), Peng and Thibodeau (2013), Peng and Thibodeau (2017), Peng and Zhang (2019), Gang, Peng and Zhang (2021), and others) as well as that of the commercial real estate market (see, e.g., Grissom et al. (1987), Pagliari (2020) and Gang, Peng and Thibodeau (2020), among others). The literature also provides ample evidence showing that the prices of spaces, both as products and properties, are affected by many local factors. Nonetheless, researchers still have much to explore on how space is priced at the granular level, for example, at the lease level. This paper develops a new hypothesis regarding pricing space from a novel perspective and finds strong supporting evidence by analyzing a newly available dataset.

The space market has two features that distinguish it from many other markets. First, tenants' demand for space is derived from their core businesses[5]. Apparently, firms may not enter a space market if they cannot afford their rents. However, for those who can afford rent, if rent variation is not significant enough, their demand for space, in terms of size and duration, is mainly derived from their core businesses and can be relatively inelastic. For example, it would be unusual for Starbucks to double the size of its store simply because rents are cheaper or for Google to cut back its Manhattan footprint because rent increases a little.

[3] According to estimates by Zillow and RedFin.
[4] According to the 2021 estimate of the National Association of Real Estate Investment Trusts.
[5] Leishman and Watkins (2004) shows that size is one of key considerations when firms choose their office occupancy.

Empirically, tenants' demand can appear relatively constant under normal market conditions, conditional upon they are already renting in the market.

Second, landlords' supply of space is rigid in the short term, both at the aggregate and individual building levels. This is particularly true in well-developed and highly regulated markets with little vacant land to develop and too many or too strict regulations preventing landlords from expanding their buildings. In this sense, at least in the short term, both the total supply of space in the market and the space each building provides can be highly inelastic.

Because of these two features, the matching between tenants' demand for space and landlords' supply of space is like jigsaw puzzle games. Each building can be considered a jigsaw board, and leases can be considered jigsaw pieces with various sizes and expiration days. When existing leases expire, their corresponding pieces disappear, and vacancy appears on the boards (buildings) they used to occupy. New jigsaw pieces appear when new or returning tenants come to the market demanding space with specific sizes and terms. Landlords with vacancies in their buildings would search and compete for new leases to fill their buildings, just like players looking for new jigsaw pieces to fill their boards.

While we are not formally modeling the above mechanism in this paper, we derive from it and test a hypothesis regarding rents. Still using jigsaw puzzle games as the analogy, we hypothesize that holding constant landlords' demand for jigsaw pieces with a specific size and term, the more abundant such jigsaw pieces, the less valuable they are for landlords. This is because landlords do not need to compete as intensively for them if similar pieces are abundant and readily available. In other words, tenants who bring to the market a lease with a specific size and term that is already abundant (readily available) in the market would need to pay higher rents. We call this the Abundance Premium.

We could also look at the Abundance Premium from a more traditional perspective, which treats space as the product. Imagine two firms needing office spaces in Manhattan. Firm A needs 3,000 square feet for 3 years, and Firm B needs 100,000 square feet for 10 years. Since each firm is more likely to compete with tenants with similar demands, these two firms are likely to compete with different sets of tenants. Consequently, these two firms' market segments can have different demands for space. Also, the number of 3,000-square-foot slots the market can provide is likely different from the number of 100,000-square-foot slots it can provide. Therefore, these two firms' market segments can have different supplies of space. Suppose 500 tenants have similar demand and are competing with Firm A, and only 20 are competing with Firm B. We hypothesize that, in equilibrium, Firm A would have to pay higher rents than Firm B, holding constant other rent-affecting factors, including space supply. This is the Abundance Premium, which is essentially a demand-side effect.

A novel dataset of office leases provided by CompStak Inc. allows us to measure lease Abundance and test the presence of the Abundance Premium. We focus on the class A office market as tenants in this market tend to be less financially constrained so that they can afford rents under normal market conditions, and their demand for space may appear to be constant and is easy to measure. We analyze the five largest markets: Los Angeles - Orange - Inland (LA), Bay Area (Bay), Dallas - Ft. Worth (Dallas), Washington DC (DC), and New York City (NYC) from 2010 to 2019. These markets are more developed than many smaller markets, and thus, the space supply tends to be less volatile over time.

We calculate lease Abundance separately for each market. Within each market, for each lease, we (1) count the number of leases in its market with similar (-0.1 to +0.1) size and terms, both of which are demeaned log values, and then (2) divide it by the total number of leases in the market. The interpretation is straightforward. For example, a lease with an Abundance of 1% means that 1% of all leases have a similar size and terms as this lease. We also calculate lease Abundance using a longer range of similarity (-0.3 to +0.3) and use it in robustness checks.

To justify using the whole sample period to calculate lease Abundance, we need to verify that tenants' demand for space, and thus lease Abundance, is mainly stable across time in the sample period. We split the sample period into the early and later half and calculate the Abundance for each lease using similar leases in each subperiod. Specifically, for a lease, its Early Abundance (Late Abundance) equals the number of similar leases in the early (late) half divided by the total number of leases in the early (late) half. We regress the Later Abundance of each lease against its Early Abundance for the whole sample and each of the five markets. We find positive and statistically significant coefficients of Early Abundance, which are close to 1. This supports the notion that tenants' demand for space and the Abundance measure for each lease are mostly stable over time.

It is worth noting that, for a lease that commences in the early half of the sample period, its Early Abundance is "actual," and Late Abundance is "counterfactual." For a lease that commences in the later half, its Late Abundance is "actual," and Early Abundance is "counterfactual." We regress the counterfactual Abundance against the actual Abundance and find that the actual Abundance coefficients are statistically significant and close to 1. This further shows that lease Abundance is stable during the sample period.

Two things are worth noting when we test the existence of the Abundance Premium. First, each tenant competes with other tenants with similar demands and those with different demands. Therefore, it is important to control the demand for space in each tenant's segment unrelated to Abundance. Second, rents are certainly affected by the supply of space, which is difficult to measure precisely, as all landlords may simultaneously solve their own optimization problems to decide how to allocate their vacant space to different tenants. Nonetheless, controlling the space supply in each tenant's market segment is essential.

Using data from the five markets, we build and estimate a modified hedonic model that carefully controls for factors that affect rents, including lease characteristics, building characteristics, tenant characteristics, and fixed effects of location and time. We find that lease Abundance significantly affects office rents. When Abundance increases by 100 basis points, the monthly rent per square foot increases by about \$0.03. This result is robust across regions and time, as well as specifications in which we use different measures of Abundance, including those calculated using a longer range of similarity in size and terms (-0.3 to +0.3). Furthermore, using alternative Abundance measures that are calculated based on lease size and terms separately, we find that size-based Abundance significantly affects rents, but term-based Abundance does not. This suggests that it is primarily tenants' competition for space size, not the duration of using it, that drives the Abundance Premium.

We then investigate possible heterogeneity in Abundance Premium across leases with different sizes, different terms, and hosted by buildings with different sizes. We find that Abundance Premium is stronger, both economically and statistically, for leases with larger sizes. We find no evidence of linear relationships between the Abundance Premium and lease terms. Finally, we find that Abundance Premium is stronger, both economically and statistically, for leases that are hosted by larger buildings.

The rest of the paper is organized as follows. Section 2 describes the data; Section 3 defines, calculates, and validates the lease Abundance; Section 4 presents our empirical model; Section 5 presents the main results; Section 6 conducts a set of robustness checks and heterogeneity analyses; and Section 7 concludes.

2. Related Literature

This paper sits in the heart of real estate segmentation literature. The real estate market is well known for segmentation and heterogeneity mainly due to its unique immobile physical attributes and heterogeneous preferences by users and investors (Geltner & Miller, 1975). The extensive literature on real estate segmentation is rooted in the urban economics of housing markets, where housing prices were found to vary in different locations due to heterogeneous demand and slow changes in supply across geographic submarkets (Straszheim, 1975). Goodman (1978) points out that housing price can vary within a metropolitan area or even within submarkets by different structure or neighborhood amenities after extending hedonic price analysis to market segmentation. Then, great efforts have been put in place to understand housing price variation on different dimensions of segmentation beyond location (Maclennan & Tu (1996); Bourassa et al. (1999, 2003); Peng & Thibodeau (2013, 2017); Gang et al. (2021) among others.) and ways to define submarket boundaries for housing (Dale-Johnson (1982), Orford (2000, 2002), Piazzesi et al. (2020) and more)

On the commercial side, segmentation is first studied to mainly understand the diversification of real estate portfolios. Variations in commercial real estate risk and return are commonly documented across property types, geographical regions, and local economic conditions to demonstrate diversification benefits within the real estate (Miles & Cue (1982); Hartzell et al. (1986, 1987); Grissom et al. (1987); Goetzmann & Wachter (1995) etc.). Later, researchers also found that commercial real estate is segmented in a more specific way. For instance, researchers demonstrates property submarkets by green certification (Eichholtz et al. (2010); Wiley et al. (2010) etc.). Fuerst & Marcato (2012) uses cluster analysis to identify segments by property attributes such as size, lease terms, number of tenants and tenant concentration and find it better predict the financial performance of commercial real estate than conventional two dimensional segments by region and property sectors. Geltner & Minne (2017) documents that not only commercial real estate price level differs across segments; price dynamics and risk-return relationship also vary among different price segments. Studies also show significant price variation by quality and extreme attributes in the hotel sector (Beracha et al. (2018); Das et al. (2018)). Besides physical attributes and spatial or locational characteristics, commercial real estate market is also recently found fragmented by investor characteristics and preferences in the search and valuation process (Costa et al. (2018); Gang et al. (2020); Ghent (2021); Cvijanović et al. (2022)). [6]

[6] Goetzmann et al. (2021) summarize most recent studies on segmentation and price variation drivers in both housing and commercial real estate asset markets and call for richer search models with underlying asset details to understand segmentation and price formation.

However, most of the commercial real estate segmentation literature is centered around the capital market and asset market, where real estate is an asset class. Knowledge in market segmentation of commercial real estate in the space market is limited beyond conventional factors like locational, spatial, property sectoral or sub-sectoral, hedonic characteristics and lease types (Pollakowski et al. (1992); Wolverton (1999); Dunse et al. (2001, 2002); Hardin & Carr (2006); Hendershott et al.(2013); Edelstein & Liu (2016)).

In this paper, we contribute to the literature in three ways. First, we extend the literature by looking at real estate space submarkets at a very granular level by leveraging a recently available dataset of detailed commercial real estate lease transactions. We add to the literature by proposing a novel way of segmenting the space market, in which we identify market segments for every individual lease. To do so, we group leases with similar lease attributes in terms of size and term at a narrow margin. Note, because lease size and term serve as a proxy for tenant's demand for space in quantity and time, this allows us to segment space market at lease level by specific demand and quantify competition of demand within micro segments. Lastly, by analyzing the impact of the quantity of leases with similar lease attributes on lease rent, we provide new evidence of how demand competition among close competitors affects pricing of space across micro segmentation at lease level in the real estate space market.

2 **Data**

We obtain an initial sample of 69,033 class A office leases commenced from January 2010 to December 2019 from CompStak Inc. in the top five US markets in terms of sample size: Los Angeles - Orange - Inland (LA), Bay Area (Bay) and Dallas - Ft. Worth (Dallas), Washington DC (DC), and New York City (NYC). Hereafter we refer to DC and NYC as the East region, and LA, BY, and Dallas as the West region. CompStak is a leading crowdsourced data provider for comprehensive commercial real estate data and claims that its data on leases are the most reliable and complete.[7] Unfortunately, we are unable to verify if CompStak captures the entire population of class A office leases or if their leases are completely random, which is a caveat of our analysis.

We focused on class A office leases not only because the office space market is important: almost all corporations need some office space, but also because they provide several advantages for our analysis. First and foremost, the demand for class A office space likely comes from more established firms that are less financially constrained, so it is more likely derived from those firms' core businesses and thus exogenous. This would make the class A office market suitable to test our hypothesis. Second, the office space sector is the most thoroughly covered sector by CompStak, so we have a large sample for our analysis. Third, office leases tend to have more straightforward rent schedules than other space types. For example, unlike retail leases, office leases typically do not have percentage rents that are tied to tenants' sale revenue. Consequently, we can more accurately measure office rents.

We follow the procedure below to clean the data and obtain the final sample: 1) We exclude 11 leases with percentage rents. 2) We require leases to have a term of at least 12 months but no more than 150 months. 3) We require net effective rent per month per square foot to be not less than \$1 but not more than \$10. 4) We exclude leases that were signed before their buildings were built (see, e.g., Edelstein and Liu (2016) for reasons). 5) We require leases to be signed no more than 2 years before their commencement. 6) We require leases to be in buildings of at least 5,000 square feet. 7) We require leases to have space sizes not smaller than 500 square feet and not larger than 1,000,000 square feet. It is important to note that the above procedure is to identify a relatively homogeneous market sector so we can more effectively and cleanly test our hypotheses, not create a biased and selective sample. Finally, we remove less than 2% of observations

[7] More information about CompStak can be found on: https://www.compstak.com/ .

with apparent data errors.[8] Our final sample comprises 60,730 class A office leases commenced from January 2010 to December 2019 in the five markets. Note that more than 60% of leases are in the West region (Bay, LA, and Dallas) and the rest are in the East region (NYC and DC).

Figure 1 displays the composition of our sample by markets: LA contributes the most to the sample by providing 27.6% of the total leases. Bay and Dallas respectively contribute about 16% and 13% of the sample. In the East region, DC has more class A office leases, making up 16.4% of our sample, and NYC contributes 12.2% of the leases to the sample. Figure 2 plots the shares of leases that commenced in each month from 2010 to 2019 by markets. The composition of lease shares across markets seems relatively stable through the sample period.

Table 1 reports summary statistics of some lease and building characteristics in the full sample and in each market. For the whole sample, the average net effective rent is about $3 per square foot per month, the average lease term is slightly over 5 years (64 months),[9] the average lease size is about 11,160 square feet, and the average building size is about 350,000 square feet. Across markets, leases in the East region (DC and NYC) tend to have higher rents than those in the West region. $2.94 in DC, $4.81 in NYC vs. $1.94 for Dallas, $2.67 for LA, and $3.23 for Bay. They also tend to have longer terms and be in larger buildings.

The dataset also contains useful categorical variables of leases (e.g., gross or net, new or renewed, signed in advance or not) and tenants (private or public companies). In our analyses, we use dummy variables to control the impact of these categorical variables on rents, which implicitly define a benchmark lease. The benchmark lease is 1) a gross lease (i.e., a full-service lease); 2) a newly signed instead of a renewed one; 3) not a sublease; 4) not signed before the commencement date; 5) not having a renewal option; 6) not

[8] Examples of data errors include inconsistent dates, inconsistent free rent type and free rent months, and lease space size larger than the building size.
[9] To calculate lease term, we treat leases commenced before the 15th of a month as commenced at the end of the previous month, and leases commenced on or after the 15th of a month as commencing at the end of the current month.

offering free rents; 7) not providing tenant improvement allowances; 8) with a private company tenant; 9) not having a single tenant in a building; and 10) in a building that belongs to the cohort of newest buildings in its market. Note that age cohorts are defined for each market separately. We sort all leases in our sample into five cohorts based on the age of their buildings. Each cohort contains roughly 20% of the leases and the default cohort comprises leases in the newest buildings. Table 2 reports the number/percentage of leases in each category, except the building age cohorts, in the whole sample as well as in each market.

3 Lease Abundance

3.1 Definition and calculation

We calculate Abundance for each lease by (1) counting the number of leases that commenced in its market with similar space size and terms, and then (2) dividing it by the total number of leases commenced in the market. An implicit assumption we are making is that the market is in equilibrium, and all tenants' demands for space are fulfilled and matched with landlords' supply of spaces. Under this assumption, the number of leases that commenced is not only the equilibrium result but also reflects tenants' demand for space. We consider this assumption reasonable, particularly for class-A office markets where tenants are typically not financially constrained.

In our main analysis, leases are considered similar if their size (in demeaned logarithmic square feet) and term (in demeaned logarithmic months) range from 0.1 less to 0.1 more than the size and term of the target lease. This means that their size in spare feet and terms in months roughly range from 10% less to 10% more than the size and term of the target lease. While this range is ad hoc, later we show that our results are robust when we use a longer range (+/-0.3) to calculate Abundance. To visualize lease size (demeaned logarithmic square feet) and lease terms (demeaned logarithmic months), Figures 3 and 4 plot their histograms for the five markets as well as the whole sample.

Apparently, we need to select the time window in which we count similar and total leases. To see this, consider a lease that commenced in June 2015. We could choose time windows with different widths: one year, two years, or even the entire sample period. Furthermore, we can choose time windows that end in, begin in, or center in June 2015. To guide our decision, it is useful to realize that the Abundance we calculate can be considered as an estimate of a latent *true* Abundance. It is an empirical question whether this latent true Abundance remains constant or varies across time. Should it remain constant, the larger the time window, the larger the sample we use, and the more accurate our calculated Abundance. Should it vary across time, the smaller the time window, the more stable the true Abundance in the window, and the more meaningful our calculated Abundance. There is an apparent tradeoff.

We find it reasonable to use the whole sample period as the time window. This is justified if lease Abundance is mostly stable during the entire sample period, which would be true under three conditions: (1) the inventory of space/buildings is stable, (2) tenants' demand for space remains stable, and (3) the composition of tenants is stable. These conditions seem reasonable for the five markets, which are well-developed, and where the local economy did not seem to go through dramatic changes in the sample period. In fact, in unreported analyses, we find that the composition of tenants' industries is almost identical for each market through the entire sample period. In the next subsection, we further calculate Abundance using smaller time windows and show that it is highly stable across time in these markets.

Our definition of Abundance has a limitation. Note that we define similar leases as those with 10% less to 10% more space/term than the target lease. The same percentage, 10%, can mean different square feet for different leases. For example, for a lease of 5,000 square feet, 10% means 500 square feet. For a lease of 100,000 square feet, it means 10,000 square feet. Since we don't know the exact range of sizes of the leases with which each lease competes, the Abundance we calculate might differ from the latent true Abundance, and the difference may vary across leases with different sizes. Unfortunately, there is no easy solution to this problem as it involves unobservable variables, so this is a caveat of our analysis.

To visualizes the Abundance we calculate, Figure 5 plots each lease's Abundance against its size and terms, for each of the five markets as well as the whole sample. Table 3 summarizes the mean, standard deviation, and quintiles of Abundance for leases in the whole sample as well as in each of the five markets. Abundance is reported in percentage points and ranges from 0 to 100. In other words, a lease with an Abundance of 1 has 1% of leases in the market that have similar size and terms with it. Note that Abundance is always calculated for each city separately even if we report their statistics for the whole sample. Among the five markets, NYC and Dallas have the highest average Abundance of 1.26 and 1.25. DC and Bay have the lowest average Abundance of 0.95 and 1.07. In terms of standard deviations of Abundance, LA and Dallas have the largest standard deviation of 1.05. DC and Bay have the smallest standard deviations of 0.75 and 0.87. This table also shows great variation in Abundance across leases. For example, for the whole sample, the minimum of Abundance is 0.01, which means there are only 0.01% of leases that are similar, while the maximum is 3.98, which means there are about 4% of leases that are similar.

3.2 Validation

Note that we calculate the Abundance of each lease by dividing the number of similar leases by the number of all leases *in the entire sample period*. Using the entire sample period as the time window to count leases is sensible if the Abundance is stable across time. The Abundance would be stable if three variables remain stable: (1) the inventory of space/buildings, (2) individual tenants' demand for space in terms of sizes and terms, and (3) the composition of tenants in the market. The three conditions are likely true because (1) 10 years is not necessarily a long term for real estate as it takes many years to develop new buildings or expand existing buildings, particularly in these well-developed (limited vacant land) and strictly regulated (long process to get permits) markets, and (2) tenants' core businesses may not have experienced significant enough changes so that they dramatically changed their demand for space, and (3) in unreported analysis, the composition of tenants' industries in each market is almost identical through the sample period. Nonetheless, we directly test whether Abundance is indeed stable across time.

To do so, we calculate two versions of Abundance using smaller time windows for each lease. We first split all leases into two groups: early subsamples, which comprise leases commenced in the early half of the sample period (i.e., before 2015), and late subsamples, which comprise leases commenced in the late half of the sample period (in and after 2015). Then, we calculate Early Abundance for each lease by dividing the number of similar leases in the early subsample by the total number of leases in the early subsample. Similarly, we calculate Late Abundance for the same lease by dividing the number of similar leases in the late subsample by the total number of leases in the late subsample. Should Abundance be stable across time, we would see a clear positive relationship between the two versions of Abundance for the same lease, regardless of whether it itself commenced in the early or late half of the sample period.

Figure 6 plots the Late Abundance against the Early Abundance for all leases in each of the five markets and the whole sample. We notice a clear positive relationship between Early and Late Abundance, though this relationship seems weaker for Bay. This is possibly due to the growth of tech companies, both in their numbers and their size, in the Bay area in our sample period, which would change both the composition of tenants and their demand for space.

To formally test whether there is a positive relationship between Early and Late Abundance, we regress Late Abundance against Early Abundance for leases in the whole sample, the East region, the West region, and each of the five markets. Panel A in Table 4 reports the results of these regressions. The coefficient estimate of Early Abundance is 1.116 for the whole sample, 0.901 and 1.231 for the East and West regions, and 1.257, 1.108, 1.251, 1.145, and 0.819 respectively for LA, Bay, Dallas, DC, and NYC. All estimates are statistically significant at the 1% level. This is strong evidence that lease Abundance is generally stable across time. It is worth noting that the adjusted R2 varies across the five markets. It is 0.97 for LA, 0.93 for Dallas, 0.87 for DC, 0.83 for NYC, and 0.61 for Bay. This is consistent with Figure 6, which shows that the positive relationship between Late and Early Abundance appears to be weaker for Bay.

There is another perspective to look at the two versions of Abundance for the same lease. For leases that commenced in the early half of the sample period, the Early Abundance is *actual* (assuming the latent true Abundance is stable in the early half of the period), and the Late Abundance is *counterfactual*. At the same time, for a lease that commenced in the late half of the sample period, its Late Abundance is actual (assuming the latent true Abundance is stable in the late half of the period), and its Early Abundance is counterfactual. Should Abundance be stable across time, we would see a positive relationship between the actual and the counterfactual Abundance measures for each lease.

Panel B in Table 4 reports the results of regressions of counterfactual Abundance against actual Abundance in the whole sample, the East region, the West region, and each of the five markets. Note that in these regressions, for leases commenced before 2015, the dependent variable is Late Abundance, and the independent variable is Early Abundance. For leases commenced in or after 2015, the dependent variable is Early Abundance, and the independent variable is Late Abundance.

The coefficient estimate of actual Abundance is 0.916 for the whole sample, 0.887 and 0.928 for the East and West regions, and 0.974, 0.674, 1.017, 0.906, and 0.875 respectively for LA, Bay, Dallas, DC, and NYC. All estimates are statistically significant at the 1% level. This further corroborates the notion that lease Abundance is generally stable during our sample period, which helps justify using the entire sample period as the time window to calculate each lease's Abundance. Note that Panel B also shows variation in adjusted R2 across the five markets: 0.85 for LA, 0.82 for NYC, 0.80 for DC, 0.78 for Dallas, and 0.52 for Bay. Apparently, Bay is the market in which Abundance is the least stable across time.

4 The Empirical Model

We now analyze the impact of lease Abundance on rent. We denote by $R_{i,t}$ lease i's net effective rent per square foot in month t. We assume that $R_{i,t}$ is affected by (1) a rent index in month t, R_t, which measures the rent of a benchmark/standardized lease, (2) its Abundance, denoted by A_i, (3) control variables $\left\{X_i^p\right\}_{p=1}^{P}$ that capture each lease's differences from the benchmark lease, and (4) an error term $\varepsilon_{i,t}$.

$$R_{i,t} = R_t + \beta_A A_i + \sum_{p=1}^{P} \beta_p X_i^p + \varepsilon_{i,t} \tag{1}$$

Our model in (1) is essentially a hedonic model. However, instead of including hedonic variables on the right side, we include their demeaned values. Consequently, the time dummies no longer measure location/land values. Instead, they measure the values of a benchmark lease.

Note that the rent index R_t in (1) is the coefficient of the dummy for month t. For each lease that expires before December 2019, its dummies equal 1 for all months after its commencement month to the month it expires, and 0 otherwise. However, note that our data are right truncated: the expiration months of some leases, particularly those commenced later in our sample period, can be after 2019. To deal with this, for a lease that expires after December 2019, we let its last dummy, the one for December 2019, equal the number of months in which the lease remains effective in and after December 2019. This implicitly assumes that monthly rents in and after December 2019 are identical. This is certainly a simplifying assumption, but our results are robust when we use leases commenced in the early half of the sample period, which are less affected by the right truncation of the data.

From the CompStak data, we observe the sum of monthly rents (per square foot) for the entire lease term duration of the lease i, which we denote by S_i.

$$S_i = \sum_{t=s_i+1}^{e_i} R_{i,t} \tag{2}$$

Where s_i denotes the month at the end of which the lease i commences, and e_i represents the month at the end of which the lease expires. Plug equation (1) into (2) and denote by T_i the duration/term[10] of lease i, which equals $e_i - s_i$, and we have the following.

$$S_i = \sum_{t=s_i+1}^{e_i} R_t + \beta_A(T_i \times A_i) + \sum_{p=1}^{P} \beta_p\left(T_i \times X_i^p\right) + \sum_{t=s_i+1}^{e_i} \varepsilon_{i,t} \tag{3}$$

Note that the coefficient of $T_i \times A_i$, β_A, is the Abundance Premium, which measures the effect of lease Abundance on net effective rent per square foot per month. The null hypothesis is that $\beta_A = 0$, which means there is no Abundance Premium. If β_A is positive, we will reject the null hypothesis and claim that Abundance Premium exists.

In addition to the month dummies and A_i, we include in the model a variety of variables to control for their impact on rents via their effects on either the demand for or the supply of space. Among them, the most important and intriguing variable is probably lease size, which is measured with demeaned (by market) log square feet. The size of a lease can help capture both demand for and supply of space in the lease's segment. First, the supply of space, in terms of the number of leases with specific sizes the market can potentially accommodate, seems a decreasing function of lease size. This is simply because, given the same amount of vacant space, the market can accommodate fewer larger leases than smaller leases, as small pieces of vacant spaces in different buildings cannot be assembled to accommodate large leases (unless tenants are willing to split their demand for space into multiple smaller pieces).

Second, lease size may also help capture demand for space. Note that, at any given time point, holding constant all tenants seeking space in the market, tenants who seek larger spaces potentially face more competitors, because they compete with not only tenants who demand similar spaces but also those who demand smaller spaces. This is because large vacant spaces can accommodate both large and small leases,

[10] We use term and duration interchangeably.

but small vacant spaces cannot accommodate larger leases. In equilibrium, whether landlords choose to host fewer larger leases or more smaller leases is a complicated question that this paper does not intend to answer. Nonetheless, it seems reasonable to argue that the demand for space, in terms of the number of tenants seeking space, in a lease's market segment is an increasing function of the lease's size.

The notion that the supply decreases with lease size and the demand increases with lease size seems to suggest that rents may increase with lease size. However, this is not necessarily true as there are other reasons why lease size may affect rents. For example, larger space per tenant may lead to economy of scale in landlords' searching and matching with new tenants (e.g., lower due diligence cost per square foot) and property management. Consequently, rents may decrease with lease size. It is also worth noting that lease size might be correlated with tenants' attributes. For example, more established tenants may demand larger space, and they may also have lower credit risk at the same time. In this case, larger leases may command lower rents. Overall, the aggregate effect of lease size on rents is an empirical question that we do not focus on, so we simply include lease size as a control variable. Note that we also include quadratics of lease size in unreported robustness checks, and our results about Abundance Premium remain strong.

Among other control variables, we include lease terms in demeaned (by market) log months. We also include dummies for submarkets within each market (e.g., Chelsea, NYC) to control for time-invariant location attributes. The base group of the submarket for the whole sample is Airport Area in LA, which comprises the most observations in the full sample. When we estimate the model for each market, we have one submarket as a base group too. We further include dummies for tenants' industries to control for industry-related factors such as credit risk. The base group of tenant industries for the entire sample is Media, which has the most observations among all industries. We also have a base group of industries in each of the five markets.

Other control variables include dummies for lease characteristics: net leases, renewed leases, subleases, leases signed in advance, renewal options, free rents for initial months, and tenant improvement allowances. We also include building size in demeaned (by market) log square feet and building age cohort dummies as both might also affect rents. For example, larger buildings can accommodate more leases and have more flexibility in allocating their spaces than smaller buildings, so they may be able to command higher rents. Newer buildings may have better amenities so they may command higher rents as well. We further include a dummy for public firm tenants in case landlords view them differently from private firms. Note that, in general, we don't argue for any specific relationships between these control variables and rents. Instead, we include them in our model to control for their effects.

5 Abundance Premium

5.1 Baseline results

We first estimate the model in (3) with lease Abundance calculated based on similarity in both lease size and terms. Since the model includes many control variables, to present our results more clearly, we report coefficient estimates of $T_i \times A_i$ and three continuous control variables – lease size, lease term, and building size, as well as sample size and adjusted R2 in Table 5, and coefficient estimates of dummy variables in Table 6. Note that we use percentage points of Abundance in all regressions. For example, the value of A_i is 1 if the Abundance is 1%.

Tables 5 and 6 report the results of six regressions. The first regression serves as a benchmark, and it includes all control variables but not $T_i \times A_i$. The second regression is our baseline model, and it adds $T_i \times A_i$ to the benchmark regression, with Abundance calculated using the time window of the whole sample period. The third and the fourth regressions are otherwise identical to the baseline/second but use leases from the East and West regions respectively. The fifth and sixth regressions are also like the second but use leases commenced in the early and late half periods respectively. The fifth regression uses Early Abundance, and the sixth regression uses Late Abundance. Note that we do not estimate the model for each market, because the large number of dummies, including the month dummies, submarket dummies, and tenant industry dummies, dramatically reduces the degree of freedom and can lead to insignificant statistical results despite the existence of the Abundance Premium.

Table 5 provides very strong evidence for the Abundance Premium. In our baseline regression, the coefficient of $T_i \times A_i$ is 0.031. This means that when the Abundance increases by 100 basis points, say from 1% to 2%, the net rent per square foot per month increases by about \$0.03. This effect is statistically significant at the 1% level. In the two regressions for the East and West regions, the coefficient is 0.073 for the East region and 0.014 for the West region. In the two regressions for the early and late halves of the sample period, the coefficient is 0.035 for the early half and 0.021 for the late half. All these coefficients are statistically significant at the 1% level.

Table 5 also reports the coefficient of lease size, which is measured with demeaned (by market) log square feet. In all six regressions, the coefficient of lease size is always negative. It is -0.083 in the benchmark regression, -0.077 in the baseline regression, -0.082 in the East region, -0.076 in the West region, -0.077 in the early period, and -0.084 in the late period. All estimates are statistically significant at the 1% level. This is clear evidence that larger leases command lower rents, though we do not suggest causation nor intend to investigate or disentangle different reasons why this is the case. Table 5 also reports the coefficient of lease term, which is measured with demeaned (by market) log months. Note that the coefficient is insignificant except for the second half of the sample period, for which the coefficient is 0.086 and statistically significant.

Table 5 further reports the coefficient of another continuous variable – building size, which is measured with demeaned (by market) log square feet of the building a lease is in. The coefficient is 0.120 in the benchmark regression, 0.122 in our baseline regression, 0.204 in the East region, 0.061 in the West region, 0.152 in the first half of the sample period, and 0.103 in the second half of the sample period. All estimates are statistically at the 1% level. This is strong evidence that leases in larger buildings have higher rents.

This can be due to many possible reasons. Among them, landlords of larger buildings have more options to allocate their space, to fewer larger leases or more smaller leases for example. Tenants who need large spaces, on the other hand, can find such spaces only in larger buildings but not in smaller buildings. This asymmetry may give landlords of large buildings more bargaining power when they negotiate with tenants, which may lead to higher rents.

Table 6 reports the coefficients of dummy variables in the same six regressions. Here we discuss the coefficients that are statistically significant across all regressions and speculate on the reasons behind the sign of each coefficient. First, net leases carry lower rents compared to gross leases, partly because landlords only need to cover none or part of the operating expenses incurred by tenants, hence requiring lower compensation compared to gross leases when landlords pay for all costs. Second, we observe higher rents for renewed leases than newly signed leases, probably because the reason why tenants want to renew is that they have a good match with the buildings. Consequently, they are willing to pay a premium to stay. Third, subleases have lower rents, which probably reflects the fact that tenants may have weaker bargaining power when subleasing their space or they are less patient in searching for tenants. It could also reflect unobserved quality differences between subleased space and non-subleased space (see, e.g., Ling, Naranjo and Scheick (2022)). Fourth, tenants pay lower effective rents in leases with concessions, either via free rents for initial months or tenant improvements provided by the landlords. This might reflect weaker demand for space in those buildings. Fifth, public companies pay higher rents, which may be due to an unobserved higher quality of the space they occupy, or they have lower risk than private firms. Finally, the coefficients of building age dummies for cohorts 1 to 4 are all negative. This shows that older buildings command lower rents, possibly due to the lower quality of fewer amenities they have.

5.2 Source of the Abundance Premium: size or terms

Now we investigate whether the Abundance Premium mostly originates from lease size or lease terms. In other words, do tenants pay higher rents because they compete more for the size of the space or more for the duration of the time in which they occupy the space? Related to this, note that the lease size can be more exogenous than lease terms. For example, a tenant's core business may dictate how much space it needs without too much flexibility, but the tenant could choose to sign a lease with a shorter term and then renew if it anticipates rents to decrease in the future.

We run the same six regressions in Tables 5 and 6 by using a lease Abundance calculated based on similarity in size only. This means that, when we count similar leases to calculate lease Abundance, we ignore lease terms and count all leases with similar size (+/-0.1). Table 7 reports the coefficient estimates of $T_i \times A_i$, lease size, lease term, and building size of the six regressions, and we no longer report coefficients of dummy variables as they are very similar to those in Table 6.

We observe positive coefficients of $T_i \times A_i$ in the second to the sixth regressions. The coefficient, which measures the Abundance Premium, is 0.015 for the whole sample, 0.024 in the East region, 0.009 in the West region, 0.018 in the early half period, and 0.011 in the second half period. All coefficients are significant at the 1% level. This is strong evidence that the Abundance calculated based on size only still increases office rents. Note that the coefficients of lease size, lease term, and building size are similar to those in Table 5.

We then calculate Abundance based on similarity in lease terms only: counting leases with similar terms and ignoring size, and we run the same regressions. In unreported regressions, we find no evidence for the effects of the Abundance by lease terms on rents. This is consistent with the notion that the source of Abundance Premium is tenants' competition for space size, not their competition for lease terms.

6 Robustness and Heterogeneity

6.1 Abundance calculated with a longer range of similarity

In our baseline analysis, we calculate the Abundance for each lease by counting leases with their size and terms ranging from 0.1 less to 0.1 more than the target lease's size and term. As this choice of the range from -0.1 to 0.1 is ad hoc, we now investigate whether our finding of Abundance Premium is robust to this choice. To do so, we recalculate the Abundance for each lease using a longer range: from 0.3 less to 0.3 more than each lease's size and term. We then estimate the same six regressions in Table 5 using this alternative Abundance measure and report the coefficient estimates of $T_i \times A_i$ and the coefficients of lease size, lease term, and building size in Table 8. Note that the first regression in Table 8 is the same as the first regression in Table 4.

Table 8 shows positive coefficients of $T_i \times A_i$ in the second to the sixth regressions. The coefficient, which measures the Abundance Premium, is always positive: 0.006 for the whole sample, 0.017 in the East region, 0.002 in the West region, 0.006 in the early half of the sample period, and 0.004 in the late half of the sample period. The coefficients are statistically significant at the 1% level for the whole sample, the East region, and the early half period, at the 5% level in the late half of the period, and at the 10% level for the West region. Overall, it seems that the Abundance Premium still exists even if we use a longer range of similarities to calculate lease Abundance. However, the results are weaker with the longer range, possibly because longer ranges measure tenants' competition less accurately (an economic reason) or lead to smaller variation in the Abundance[11] and thus lower power of the test (a statistical reason).

6.2 Heterogeneity in Abundance Premium

We conduct three heterogeneity analyses. First, note that in our baseline analysis, we use lease size to control for many factors that may affect rents, including the demand for (i.e., higher demand in a larger lease's segment) and the supply of space (i.e., a lower supply in a larger lease's segment). However, by including the lease size itself in the model and quadratics in unreported robustness checks, we only control

[11] To see this, note that if the range is long enough to cover all leases, Abundance will be 100% for all leases and there is no variation in Abundance across leases.

the linear and quadratic relationships between lease size and rents. It is possible that (1) the relationship between lease size and rents is non-linear and complicated, and (2) the Abundance Premium varies across leases with different sizes. Therefore, we split the whole sample of leases into three groups with roughly equal numbers of leases based on their sizes in their own markets: the first tercile comprises the smallest one-third of leases, and the third comprises the largest one-third of leases.

We estimate the model in (3) for each tercile and report the coefficient of $T_i \times A_i$, which measures the Abundance Premium, in Panel A of Table 9. For the smallest tercile, the Abundance Premium is 0.007, but it is not statistically significant. For the medium tercile, the premium is 0.018 and statistically significant at the 5% level. The premium for the largest tercile is 0.038, which is statistically significant at the 5% level. These results seem to suggest that the Abundance Premium is stronger both economically and statistically for larger leases.

This result might reflect heterogeneity in the demand for and supply of space across lease sizes. Note that smaller leases face a higher supply than larger ones because buildings that can accommodate larger leases can always accommodate smaller leases but buildings that can accommodate smaller leases can not necessarily accommodate larger leases. A disturbance in demand in smaller leases' market segment, say, a shock to their Abundance, can be absorbed by both small and large buildings and thus may have smaller effects on rents. The same shock to larger leases' Abundance, on the other hand, can only be absorbed by large buildings and thus may have larger effects on rents.

However, the insignificance of the Abundance Premium for small leases can also be spurious and caused by our calculation of lease Abundance. Note that, when we calculate lease Abundance, we define similar leases as those with 10% less to 10% more space/term. For smaller leases, if this range of 10% less to 10% more is too short, we would underestimate the true Abundance, and the variation of the true Abundance can be much smaller than the variation of our calculated Abundance. To see this, ignore other rent-affecting factors and consider an extreme scenario: leases in the smallest tercile all compete with each other so they are all "similar" leases, but they don't compete with leases in the medium or large tercile. In this case, the latent true Abundance for all small leases is identical (33%) and there is no variation. Consequently, rents would be constant across all small leases as they have the same true Abundance. When we regress rents against our *calculated* Abundance, which has positive variation, we get a coefficient of 0. However, this is a spurious result and should not be interpreted as evidence of the absence of the Abundance Premium.

Since our Abundance measure is defined based on both lease size and terms and we find a relationship between the Abundance Premium and lease sizes, it seems natural to ask whether the Abundance Premium also varies across leases with different terms. To answer this question, we split the whole sample of leases into three groups based on their terms: the first tercile comprises one-third of leases with the shortest terms (in each market respectively), and the third comprises one-third of leases that have the longest terms. We estimate the model in (3) for each tercile and report the Abundance Premium in Panel B of Table 9. For the tercile of shortest leases, the Abundance Premium is 0.059. For the medium tercile, the premium is 0.020. For the tercile of longest leases, it is 0.064. All three estimates are statistically significant at the 1% level. The result shows that (1) the Abundance Premium is significant across leases with different terms, and (2) there does not seem to be a linear relationship between the Abundance Premium and lease terms.

The third possible heterogeneity we analyze pertains to building sizes. Landlords of larger buildings have an advantage over those of smaller ones: they have more flexibility in deciding which leases to accept. Specifically, larger buildings can host either fewer large leases or more small leases. But smaller buildings may not be able to host large leases at all. In this sense, landlords of large buildings may have more bargaining power when negotiating with tenants than the landlords of smaller ones. This might allow large buildings to not only charge higher rents but also command higher Abundance Premiums. While there may be other reasons why the Abundance Premium might vary across buildings with different sizes, it is ultimately an empirical question of whether the Abundance Premium varies with building size.

Once again, we put leases into three groups based on their building sizes. The first comprises about one-third of leases that are in the smallest buildings, and the third comprises about one-third of leases that are in the largest buildings. We estimate the model in (3) for each tercile and report the Abundance Premium in Panel C of Table 9. The Abundance Premium shows a clear positive relationship with building size. It equals 0.004 for leases in small buildings and is not statistically significant. For leases in buildings with medium sizes, the Abundance Premium equals 0.018 and is significant at the 5% level. For leases in large buildings, it equals 0.054 and is significant at the 1% level. Therefore, empirically, it seems fair to conclude that the Abundance Premium is stronger both economically and statistically for leases in larger buildings.

7 Conclusion

A recently available novel dataset of office leases gives us a rare opportunity to better understand the pricing of space at a very micro level: the lease level. Under the premise that (1) tenants' demand for space is mostly derived from their core businesses and thus mostly exogenous, and (2) the inventory of buildings, which affects the supply of space, is mostly rigid in the short term and in markets that are well developed (not much vacant land left) and have strict regulations (costly and time-consuming to develop), we argue that the matching between leases with buildings is like jigsaw puzzle games. Leases are like jigsaw pieces that are generated exogenously. Landlords compete and search for leases to fill their buildings, just like jigsaw players compete for pieces to fill their boards. We hypothesize that more abundant jigsaw pieces are less valuable for players. This means that tenants of more abundant leases, which are less valuable for landlords, need to pay higher rents. We call this relationship the Abundance Premium.

Our hypothesis can also be interpreted from a more traditional perspective. Note that the space market is likely segmented for leases with different sizes and terms: when searching for space, each tenant competes mostly with other tenants with similar demands for space instead of tenants with different demands. In this framework, our Abundance Premium hypothesis is that where similar leases are more abundant, tenants face more competition from other tenants with similar demands; therefore, they are likely to pay high rents, holding constant other factors including the supply of space.

We propose a novel variable called lease Abundance to measure this type of competition. Mathematically, for each lease in a market, the Abundance of this lease equals the percentage of leases in the market with similar sizes and terms. Apparently, we need to define "similarity" and select the time window in which we count leases. To calculate lease Abundance in our main analysis, a lease is considered similar if its size and term range from 10% less to 10% more than the size and term of the target lease. While this 20% range is ad hoc, we show that the Abundance Premium remains strong when we use a longer range of similarity to calculate lease Abundance.

Realizing that our calculated Abundance can be considered as an estimate of the latent true Abundance, there is a tradeoff in selecting the time window. On one hand, the wider the window, the larger the sample of leases we have, and possibly the more accurate our estimate. On the other hand, the wider the window, the more likely the latent Abundance varies, and the less meaningful our estimate is. Empirically, we find that our calculated Abundance is very stable across time. By dividing the sample period of 2010 to 2019 into two equal subperiods, we find that the Abundance measure calculated in each subperiod for the same lease is highly correlated. Therefore, in our main analysis, we calculate Abundance for each lease using the entire sample period as the time window in which we count similar and total leases.

Using 60,730 class-A office leases in the five largest US markets from 2010 2o 2019, we calculate Abundance for each lease and estimate an empirical model to test whether lease Abundance affects rents. The model uses month dummies to capture the time variation of the rent of a benchmark lease and carefully controls for lease characteristics, particularly lease size, which is likely correlated with both the demand for and the supply of space in each lease's market segment. It also controls for building characteristics, including location (via submarket fixed effects), and many tenant characteristics. We find very strong evidence that lease Abundance significantly increases rents: when Abundance increases by 100 basis points, rents increase by $0.03 per month per square foot. This effect is statistically significant in the whole sample, the markets in the East and West regions, and the early and late halves of the sample period.

Regarding the source of the Abundance Premium, we find that the lease size, not the lease term, seems to cause the premium. This means that if we define similar leases based on size only, the Abundance Premium exists. But if we define similar leases based on their terms only, we find no evidence of the Abundance Premium. In terms of heterogeneity in the Abundance Premium, we find that it is stronger for larger leases, both economically and statistically, but it is equally significant for leases with different terms. Across buildings with different sizes, we find that the Abundance Premium is stronger for leases in larger buildings, both economically and statistically.

Our results provide novel insights into the pricing of space at a very micro level and reveal the role of tenants' competition in determining rents. This is the first time the literature documents this lease-level relationship, thanks to a recently available dataset. Our results suggest that there can be more to explore at the very micro level in highly segmented markets of heterogeneous goods.

References

Beracha, E., Hardin, W. G., & Skiba, H. M. (2018). Real Estate Market Segmentation: Hotels as Exemplar. The Journal of Real Estate Finance and Economics, 56(2), 252–273. https://doi.org/10.1007/s11146-017-9598-z

Bourassa, S. C., Hamelink, F., Hoesli, M., & MacGregor, B. D. (1999). Defining Housing Submarkets. Journal of Housing Economics, 8(2), 160–183. https://doi.org/10.1006/jhec.1999.0246

Bourassa, S. C., Hoesli, M., & Peng, V. S. (2003). Do housing submarkets really matter? Journal of Housing Economics, 12(1), 12–28. https://doi.org/10.1016/S1051-1377(03)00003-2

Costa, O., Fuerst, F., & Mendes-da-Silva, W. (2018). Are corporate office buildings priced differently? Journal of Property Investment & Finance, 36(4), 348–365. https://doi.org/10.1108/JPIF-01-2018-0004

Cvijanović, D., Milcheva, S., & van de Minne, A. (2022). Preferences of Institutional Investors in Commercial Real Estate. The Journal of Real Estate Finance and Economics, 65(2), 321–359. https://doi.org/10.1007/s11146-020-09816-y

Dale-Johnson, D. (1982). An alternative approach to housing market segmentation using hedonic price data. Journal of Urban Economics, 11(3), 311–332. https://doi.org/10.1016/0094-1190(82)90078-X

Das, P., Smith, P., & Gallimore, P. (2018). Pricing Extreme Attributes in Commercial Real Estate: The Case of Hotel Transactions. The Journal of Real Estate Finance and Economics, 57(2), 264–296. https://doi.org/10.1007/s11146-017-9621-4

Dunse, N., Leishman, C., & Watkins, C. (2001). Classifying office submarkets. Journal of Property Investment & Finance, 19(3), 236–250. https://doi.org/10.1108/14635780110387592

Dunse, N., Leishman, C., & Watkins, C. (2002). Testing for the Existence of Office Sub-markets: A Comparison of Evidence from Two Cities. Urban Studies, 39(3), 483–506.

Edelstein, R. H., & Liu, P. (2016). The Economics of Commercial Real Estate Preleasing. The Journal of Real Estate Finance and Economics, 53(2), 200–217. https://doi.org/10.1007/s11146-015-9515-2

Eichholtz, P., Kok, N., & Quigley, J. M. (2010). Doing well by doing good? Green office buildings. American Economic Review, 100(5), 2492-2509.

Fuerst, F., & Marcato, G. (2011). Re-Thinking Commercial Real Estate Market Segmentation (SSRN Scholarly Paper 1692953). https://doi.org/10.2139/ssrn.1692953

Gang, J., Peng, L., & Thibodeau, T. G. (2020). Risk and Returns of Income Producing Properties: Core versus Noncore. Real Estate Economics, 48(2), 476–503. https://doi.org/10.1111/1540-6229.12208

Gang, J., Peng, L., & Zhang, J. (2021). Are Pricier Houses Less Risky? Evidence from China. The Journal of Real Estate Finance and Economics, 63(4), 662–677. https://doi.org/10.1007/s11146-020-09792-3

Geltner, D. M., & Minne, A. V. D. (2017). Do Different Price Points Exhibit Different Investment Risk and Return in Commercial Real Estate? The Journal of Portfolio Management, 43(6), 105–119. https://doi.org/10.3905/jpm.2017.43.6.105

Geltner, D., & Miller, N. (2007). Commercial Real Estate Analysis and Investments.

Ghent, A. C. (2021). What's wrong with Pittsburgh? Delegated investors and liquidity concentration. Journal of Financial Economics, 139(2), 337–358. https://doi.org/10.1016/j.jfineco.2020.08.015

Goetzmann, W. N., Spaenjers, C., & Van Nieuwerburgh, S. (2021). Real and Private-Value Assets. The Review of Financial Studies, 34(8), 3497–3526. https://doi.org/10.1093/rfs/hhab035

Goetzmann, W. N., & Wachter, S. M. (1995). Clustering Methods for Real Estate Portfolios. Real Estate Economics, 23(3), 271–310. https://doi.org/10.1111/1540-6229.00666

Goodman, A. C. (1978). Hedonic prices, price indices and housing markets. Journal of Urban Economics, 5(4), 471–484. https://doi.org/10.1016/0094-1190(78)90004-9

Goodman, A. C., & Thibodeau, T. G. (1998). Housing Market Segmentation. Journal of Housing Economics, 7(2), 121–143. https://doi.org/10.1006/jhec.1998.0229

Goodman, A. C., & Thibodeau, T. G. (2003). Housing market segmentation and hedonic prediction accuracy. Journal of Housing Economics, 12(3), 181–201. https://doi.org/10.1016/S1051-1377(03)00031-7

Grissom, T.V., Hartzell, D. and Liu, C.H. (1987), An Approach to Industrial Real Estate Market Segmentation and Valuation Using the Arbitrage Pricing Paradigm. Real Estate Economics, 15: 199-219. https://doi-org.ezaccess.libraries.psu.edu/10.1111/1540-6229.00428

Hardin, W. G., & Carr, J. (2006). Disaggregating Neighborhood and Community Center Property Types. The Journal of Real Estate Research, 28(2), 167–192.

Hartzell, D., Hekman, J., & Miles, M. (1986). Diversification Categories in Investment Real Estate. Real Estate Economics, 14(2), 230–254.

Hartzell, D. J., Shulman, D. G., & Wurtzebach, C. H. (1987). Refining the Analysis of Regional Diversification for Income-Producing Real Estate. The Journal of Real Estate Research, 2(2), 85–95.

Hendershott, P. H., Jennen, M., & MacGregor, B. D. (2013). Modeling Space Market Dynamics: An Illustration Using Panel Data for US Retail. The Journal of Real Estate Finance and Economics, 47(4), 659–687. https://doi.org/10.1007/s11146-013-9426-z

Leishman, C., & Watkins, C. (2004). The decision‐making behaviour of office occupiers. Journal of Property Investment & Finance, 22(4), 307–319. https://doi.org/10.1108/14635780410550876

Maclennan, D., & Tu, Y. (1996). Economic perspectives on the structure of local housing systems. Housing Studies, 11(3), 387–406. https://doi.org/10.1080/02673039608720864

Marcato, G., & Tong, L. M. M. (2023). Supply Constraints and Search Equilibrium in Office Markets. The Journal of Real Estate Finance and Economics. https://doi.org/10.1007/s11146-023-09955-y

Miles, M., & Cue, T. M. (1982). Historic Returns and Institutional Real Estate Portfolios. Real Estate Economics, 10(2), 184–199.

Orford, S. (2000). Modelling Spatial Structures in Local Housing Market Dynamics: A Multilevel Perspective. Urban Studies, 37(9), 1643–1671.

Orford, S. (2002). Valuing Locational Externalities: A GIS and Multilevel Modelling Approach. Environment and Planning B: Planning and Design, 29(1), 105–127. https://doi.org/10.1068/b2780

Pagliari Jr., J. L. (2020). Real Estate Returns by Strategy: Have Value-Added and Opportunistic Funds Pulled Their Weight? Real Estate Economics, 48(1), 89–134. https://doi.org/10.1111/1540-6229.12190

Peng, L., & Thibodeau, T. (2013). Risk Segmentation of American Homes: Evidence from Denver. Real Estate Economics, 41(3), 569–599. https://doi.org/10.1111/reec.12005

Peng, L., & Thibodeau, T. G. (2017). Idiosyncratic Risk of House Prices: Evidence from 26 Million Home Sales. Real Estate Economics, 45(2), 340–375. https://doi.org/10.1111/1540-6229.12136

Peng, L., & Zhang, L. (2021). House Prices and Systematic Risk: Evidence from Microdata. Real Estate Economics, 49(4), 1069–1092. https://doi.org/10.1111/1540-6229.12277

Piazzesi, M., Schneider, M., & Stroebel, J. (2020). Segmented Housing Search. American Economic Review, 110(3), 720–759. https://doi.org/10.1257/aer.20141772

Pollakowski, H. O., Wachter, S. M., & Lynford, L. (1992). Did Office Market Size Matter in the 1980s? A Time-Series Cross-Sectional Analysis of Metropolitan Area Office Markets. Real Estate Economics, 20(2), 302–324. https://doi.org/10.1111/1540-6229.00586

Straszheim, M. R. (1975). An econometric analysis of the urban housing market. National Bureau of Economic Research : distributed by Columbia University Press.

Watkins, C. A., 2001, The definition and identification of housing submarkets, Environment and Planning A 33, 2235-2253.

Wiley, J. A., Benefield, J. D., & Johnson, K. H. (2010). Green Design and the Market for Commercial Office Space. The Journal of Real Estate Finance and Economics, 41(2), 228–243. https://doi.org/10.1007/s11146-008-9142-2

Wolverton, M. L., Hardin, W. G., & Cheng, P. (1999). Disaggregation of Local Apartment Markets by Unit Type. The Journal of Real Estate Finance and Economics, 19(3), 243–257. https://doi.org/10.1023/A:1007884628153

Table 1. Summary statistics of continuous variables

This table presents the summary statistics of main lease and building characteristics of class A office leases that commenced from January 2010 to December 2019 in the largest five US markets.

	Mean	Std. Dev.	Minimum	25%	Median	75%	Maximum
The whole sample: 60,730 observations							
Net effective rent ($/month/square foot)	3.02	1.43	1.00	2.00	2.63	3.70	10.00
Lease term (months)	64	33	12	38	60	84	150
Lease size (1,000 square feet)	11.16	23.99	0.50	2.56	4.92	10.88	992.04
Building size (1,000 square feet)	349.48	399.00	5.20	130.33	225.03	384.29	3,600.00
LA: 19,708 observations							
Net effective rent ($/month/square foot)	2.67	1.09	1.00	1.93	2.40	3.11	9.66
Lease term (months)	59	29	12	37	60	68	150
Lease size (1,000 square feet)	9.38	17.73	0.50	2.30	4.24	9.50	550.00
Building size (1,000 square feet)	295.68	310.40	5.20	111.35	212.21	335.68	2,639.49
Bay: 11,338 observations							
Net effective rent ($/month/square foot)	3.23	1.45	1.00	2.23	2.90	3.89	10.00
Lease term (months)	52	27	12	36	49	63	149
Lease size (1,000 square feet)	10.03	22.89	0.50	2.24	4.10	9.05	612.80
Building size (1,000 square feet)	170.47	127.22	5.30	89.03	143.44	218.65	1,838.17
Dallas: 9,301 observations							
Net effective rent ($/month/square foot)	1.94	0.47	1.00	1.58	1.92	2.22	6.95
Lease term (months)	63	30	12	38	63	78	150
Lease size (1,000 square feet)	9.50	20.40	0.50	2.11	3.87	8.92	800.00
Building size (1,000 square feet)	363.83	335.87	5.24	166.02	261.99	393.28	1,957.82
DC: 11,716 observations							
Net effective rent ($/month/square foot)	2.94	0.98	1.00	2.19	2.81	3.58	9.88
Lease term (months)	76	37	12	50	66	114	150
Lease size (1,000 square feet)	14.09	29.87	0.50	3.18	6.12	13.47	900.00
Building size (1,000 square feet)	244.69	151.63	9.00	145.75	210.52	303.48	1,518.37
NYC: 8,667 observations							
Net effective rent ($/month/square foot)	4.81	1.57	1.00	3.71	4.62	5.68	10.00
Lease term (months)	79	37	12	53	70	120	150
Lease size (1,000 square feet)	14.51	30.76	0.51	3.95	7.20	14.70	992.04
Building size (1,000 square feet)	832.26	653.09	25.83	359.33	591.40	1,160.00	3,600.00

Table 2. Summary statistics of categorical variables

This table reports the number (percentage in parentheses) of leases in each category of leases in the whole sample as well as in each of the five markets. Note that T.I. stands for tenant improvements.

Market	Whole	LA	Bay	Dallas	DC	NYC
Sample size	60,730	19,708	11,338	9,301	11,716	8,667
Net lease	16,312	1,686	2,202	8,655	1,157	2,612
	(27%)	(8.6%)	(19%)	(93%)	(9.9%)	(30%)
Renewed	21,748	7,264	3,554	3,884	4,574	2,472
	(36%)	(37%)	(31%)	(42%)	(39%)	(29%)
Sublease	4,274	735	983	224	979	1,353
	(7.0%)	(3.7%)	(8.7%)	(2.4%)	(8.4%)	(16%)
Pre-signed	51,615	16,835	10,231	8,106	10,320	6,123
	(85%)	(85%)	(90%)	(87%)	(88%)	(71%)
Renew option	3,404	2,751	335	48	229	41
	(5.6%)	(14%)	(3.0%)	(0.5%)	(2.0%)	(0.5%)
Free rent	39,933	12,964	6,069	5,896	8,090	6,914
	(66%)	(66%)	(54%)	(63%)	(69%)	(80%)
T.I.	56,814	18,514	9,734	9,134	11,265	8,167
	(94%)	(94%)	(86%)	(98%)	(96%)	(94%)
Public tenant	5,455	1,676	1,160	773	1,136	710
	(9.0%)	(8.5%)	(10%)	(8.3%)	(9.7%)	(8.2%)
Single tenant	193	26	130	14	23	0
	(0.3%)	(0.1%)	(1.1%)	(0.2%)	(0.2%)	(0%)

Table 3. Summary statistics of lease Abundance

This table reports summary statistics of lease Abundance in the whole sample as well as each market.

	Mean	Std. Dev.	Minimum	25%	Median	75%	Maximum
The whole sample	1.15	0.97	0.01	0.34	0.81	1.86	3.98
LA	1.21	1.05	0.01	0.35	0.76	1.98	3.98
Bay	1.07	0.87	0.01	0.32	0.75	1.83	2.89
Dallas	1.25	1.05	0.01	0.35	0.87	2.03	3.80
DC	0.95	0.75	0.02	0.33	0.80	1.42	3.34
NYC	1.26	1.03	0.01	0.33	1.04	2.15	3.63

Table 4. Regressions validating the Abundance measure

This table reports the results of two types of regressions - (1) Late Abundance against Early Abundance and (2) counterfactual Abundance against actual Abundance – in the whole sample, the East region (DC and NYC), the West region (LA, Bay, and Dallas), and in each of the five markets. The Early Abundance of a lease is the ratio of the number of similar leases that commenced before 205 to the number of all leases that commenced before 2015. The Late Abundance of a lease is the ratio of the number of similar leases that commenced in or after 205 to the number of all leases that commenced in or after 2015. For a lease that commenced before 2015, its counterfactual Abundance is its Late Abundance, and its actual Abundance is its Early Abundance. For a lease that commenced in or after 2015, its counterfactual Abundance is its Early Abundance, and its actual Abundance is its Late Abundance. Robust standard errors are in parentheses. The stars ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Market	Who sample	East	West	LA	Bay	Dallas	DC	NYC
Sample size	60,730	20,383	40,347	19,708	11,338	9,301	11,716	8,667
Panel A: Late Abundance regressed against Early Abundance								
Intercept term	0.103***	0.149***	0.079***	0.014***	0.167***	0.154***	0.042***	0.112***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.009)	(0.005)	(0.004)	(0.007)
Early Abundance	1.116***	0.901***	1.231***	1.257***	1.108***	1.251***	1.145***	0.819***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.008)	(0.003)	(0.004)	(0.004)
Adjusted R2	0.84	0.81	0.88	0.97	0.61	0.93	0.88	0.83
Panel B: Counterfactual Abundance regressed against factual Abundance								
Intercept term	0.029***	0.065***	0.012***	0.018***	0.135***	-0.044***	0.051***	0.075***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.008)	(0.009)	(0.005)	(0.007)
Actual Abundance	0.916***	0.887***	0.928***	0.974***	0.674***	1.017***	0.906***	0.875***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.004)	(0.004)
Adjusted R2	0.77	0.81	0.76	0.85	0.52	0.78	0.80	0.82

Table 5. Test Abundance Premium: Part I

This table reports part I of the results of estimating the cross-sectional model below to test whether lease Abundance affects office rents.

$$S_i = \sum_{t=s_i+1}^{e_i} R_t + \beta_A(T_i \times A_i) + \sum_{p=1}^{P} \beta_p(T_i \times X_i^p) + \sum_{t=s_i+1}^{e_i} \varepsilon_{i,t}$$

In this model, the dependent variable S_i is the sum of the monthly rents (per square foot) for the entire lease term duration of the lease i, s_i is the month at the ed of which the lease i commences, and e_i is the month at the end of which the lease expires, R_t is the coefficient of month dummies, T_i is the lease term in months, A_i is lease Abundance, X_i^p for $p = 1, \cdots, P$ are control variables, including continuous variables - lease size (log square feet demeaned by market), lease term (log months demeaned by market), building size (log square feet demeaned by market) – and dummy variables for building age cohorts, submarkets, net leases, renewed leases, subleases, leases signed before commencement, leases with renew options, leases with free rents, leases with tenant improvement allowance, the tenant being a public firm, and the tenant being a single tenant. This table reports estimates of lease Abundance and continuous control variables, as well as sample size and the adjusted R2. Robust standard errors are in parentheses. The stars ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Benchmark	Baseline	East	West	Early	Late
Abundance		0.031***	0.073***	0.014***		
		(0.005)	(0.011)	(0.004)		
Early Abundance					0.035***	
					(0.008)	
Late Abundance						0.021***
						(0.007)
Lease size	-0.083***	-0.077***	-0.082***	-0.076***	-0.077***	-0.084***
	(0.005)	(0.006)	(0.010)	(0.006)	(0.008)	(0.008)
Lease term	0.005	0.016	-0.004	0.003	0.003	0.086***
	(0.015)	(0.015)	(0.025)	(0.017)	(0.023)	(0.021)
Building size	0.120***	0.122***	0.204***	0.061***	0.152***	0.103***
	(0.009)	(0.009)	(0.017)	(0.009)	(0.013)	(0.012)
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Submarket dummies	Yes	Yes	Yes	Yes	Yes	Yes
Tenant industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other control variables: see Table 6						
Sample size	60,730	60,730	20,383	40,347	27,423	33,307
Adjusted R2	0.95	0.95	0.95	0.95	0.95	0.96

Table 6. Testing Abundance Premium: Part II

This table reports part II of the results of estimating the cross-sectional model below to test whether lease Abundance affects office rents.

$$S_i = \sum_{t=s_i+1}^{e_i} R_t + \beta_A (T_i \times A_i) + \sum_{p=1}^{P} \beta_p (T_i \times X_i^p) + \sum_{t=s_i+1}^{e_i} \varepsilon_{i,t}$$

In this model, the dependent variable S_i is the sum of the monthly rents (per square foot) for the entire lease term duration of the lease i, s_i is the month at the end of which the lease i commences, and e_i is the month at the end of which the lease expires, R_t is the coefficient of month dummies, T_i is the lease term in months, A_i is lease Abundance, X_i^p for $p = 1, \cdots, P$ are control variables, including continuous variables - lease size (log square feet demeaned by market), lease term (log months demeaned by market), building size (log square feet demeaned by market) – and dummy variables for building age cohorts, submarkets, net leases, renewed leases, subleases, leases signed before commencement, leases with renew options, leases with free rents, leases with tenant improvement allowance, the tenant being a public firm, and the tenant being a single tenant). This table reports estimates of coefficients of dummy variables. Robust standard errors are in parentheses. The stars ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Benchmark	Baseline	East	West	Early	Late
Net lease	-0.267***	-0.265***	-0.208***	-0.319***	-0.353***	-0.305***
	(0.018)	(0.018)	(0.026)	(0.023)	(0.027)	(0.023)
Renewed	0.113***	0.117***	0.169***	0.073***	0.144***	0.093***
	(0.010)	(0.010)	(0.018)	(0.011)	(0.015)	(0.013)
Sublease	-0.377***	-0.361**	-0.454***	-0.178***	-0.443***	-0.307***
	(0.028)	(0.028)	(0.034)	(0.047)	(0.039)	(0.037)
Signed in advance	0.009	0.010	0.088***	-0.050***	-0.020	-0.063***
	(0.015)	(0.015)	(0.024)	(0.016)	(0.019)	(0.021)
Renew option	-0.004	-0.004	0.118*	0.003	0.030	0.003
	(0.020)	(0.020)	(0.061)	(0.020)	(0.023)	(0.032)
Free rent	-0.269***	-0.274***	-0.381***	-0.190***	-0.278***	-0.250***
	(0.011)	(0.012)	(0.022)	(0.013)	(0.016)	(0.016)
Tenant improvement	-0.216***	-0.217***	-0.192***	-0.214***	-0.190***	-0.104***
	(0.027)	(0.027)	(0.052)	(0.030)	(0.074)	(0.028)
Public tenant	0.067***	0.068***	0.044	0.0790***	0.059*	0.067***
	(0.018)	(0.018)	(0.032)	(0.020)	(0.026)	(0.024)
Single tenant	0.040	0.045	0.171	-0.015	0.221*	-0.106
	(0.089)	(0.089)	(0.131)	(0.098)	(0.128)	(0.109)
Age cohort 1	-0.409***	-0.409***	-0.540***	-0.166***	-0.454***	-0.329***
	(0.023)	(0.023)	(0.033)	(0.028)	(0.033)	(0.030)
Age cohort 2	-0.310***	-0.312***	-0.256***	-0.317***	-0.359***	-0.278***
	(0.017)	(0.017)	(0.033)	(0.019)	(0.025)	(0.022)
Age cohort 3	-0.315***	-0.316***	-0.291***	-0.306***	-0.322***	-0.307***
	(0.016)	(0.016)	(0.030)	(0.018)	(0.022)	(0.020)
Age cohort 4	-0.257***	-0.259***	-0.271***	-0.225***	-0.224***	-0.254***
	(0.016)	(0.016)	(0.025)	(0.019)	(0.023)	(0.020)

Table 7. Testing Abundance Premium: Abundance based on lease size only

This table reports part I of the results of estimating the cross-sectional model below to test whether lease Abundance affects office rents.

$$S_i = \sum_{t=s_i+1}^{e_i} R_t + \beta_A (T_i \times A_i) + \sum_{p=1}^{P} \beta_p (T_i \times X_i^p) + \sum_{t=s_i+1}^{e_i} \varepsilon_{i,t}$$

In this model, the dependent variable S_i is the sum of the monthly rents (per square foot) for the entire lease term duration of the lease i, s_i is the month at the end of which the lease i commences, and e_i is the month at the end of which the lease expires, R_t is the coefficient of month dummies, T_i is the lease term in months, A_i is lease Abundance that is calculated based on lease size only, X_i^p for $p = 1, \cdots, P$ are control variables, including continuous variables - lease size (log square feet demeaned by market), lease term (log months demeaned by market), building size (log square feet demeaned by market) – and dummy variables for building age cohorts, submarkets, net leases, renewed leases, subleases, leases signed before commencement, leases with renew options, leases with free rents, leases with tenant improvement allowance, the tenant being a public firm, and the tenant being a single tenant. This table reports estimates of lease Abundance and continuous control variables, as well as sample size and the adjusted R2. Robust standard errors are in parentheses. The stars ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Benchmark	Baseline	East	West	Early	Late
Abundance		0.015***	0.024***	0.009***		
		(0.003)	(0.004)	(0.003)		
Early Abundance					0.018***	
					(0.004)	
Late Abundance						0.011***
						(0.003)
Lease size	-0.083***	-0.061***	-0.059***	-0.065***	-0.057***	-0.072***
	(0.005)	(0.006)	(0.010)	(0.007)	(0.009)	(0.009)
Lease term	0.005	0.005	0.017	-0.007	0.002	0.081***
	(0.015)	(0.015)	(0.025)	(0.017)	(0.023)	(0.021)
Building size	0.120***	0.122***	0.204***	0.061***	0.153***	0.103***
	(0.009)	(0.009)	(0.017)	(0.009)	(0.013)	(0.012)
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Submarket dummies	Yes	Yes	Yes	Yes	Yes	Yes
Tenant industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other control variables: included not coefficients not reported						
Sample size	60,730	60,730	20,383	40,347	27,423	33,307
Adjusted R2	0.95	0.95	0.95	0.95	0.95	0.96

Table 8. Testing Abundance Premium: Abundance based on a longer range of similarity

This table reports part I of the results of estimating the cross-sectional model below to test whether lease Abundance affects office rents.

$$S_i = \sum_{t=s_i+1}^{e_i} R_t + \beta_A(T_i \times A_i) + \sum_{p=1}^{P} \beta_p(T_i \times X_i^p) + \sum_{t=s_i+1}^{e_i} \varepsilon_{i,t}$$

In this model, the dependent variable S_i is the sum of the monthly rents (per square foot) for the entire lease term duration of the lease i, s_i is the month at the end of which the lease i commences, and e_i is the month at the end of which the lease expires, R_t is the coefficient of month dummies, T_i is the lease term in months, A_i is lease Abundance that is calculated based on both lease size and lease term but using a longer range of similarity (+/-0.3), X_i^p for $p = 1, \cdots, P$ are control variables, including continuous variables - lease size (log square feet demeaned by market), lease term (log months demeaned by market), building size (log square feet demeaned by market) – and dummy variables for building age cohorts, submarkets, net leases, renewed leases, subleases, leases signed before commencement, leases with renew options, leases with free rents, leases with tenant improvement allowance, the tenant being a public firm, and the tenant being a single tenant. This table reports estimates of lease Abundance and continuous control variables, as well as sample size and the adjusted R2. Robust standard errors are in parentheses. The stars ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Benchmark	Baseline	East	West	Early	Late
Abundance		0.006***	0.017***	0.002**		
		(0.001)	(0.003)	(0.001)		
Early Abundance					0.006***	
					(0.002)	
Late Abundance						0.004**
						(0.002)
Lease size	-0.083***	-0.078***	-0.079***	-0.077***	-0.079***	-0.084***
	(0.005)	(0.006)	(0.010)	(0.007)	(0.008)	(0.008)
Lease term	0.005	0.016	0.017	-0.0004	0.007	0.088***
	(0.015)	(0.015)	(0.025)	(0.016)	(0.023)	(0.020)
Building size	0.120***	0.121***	0.202***	0.061***	0.152***	0.102***
	(0.009)	(0.009)	(0.016)	(0.009)	(0.013)	(0.012)
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Submarket dummies	Yes	Yes	Yes	Yes	Yes	Yes
Tenant industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other control variables: included not coefficients not reported						
Sample size	60,730	60,730	20,383	40,347	27,423	33,307
Adjusted R2	0.95	0.95	0.95	0.95	0.95	0.96

Table 9. Test Abundance Premium: heterogeneity

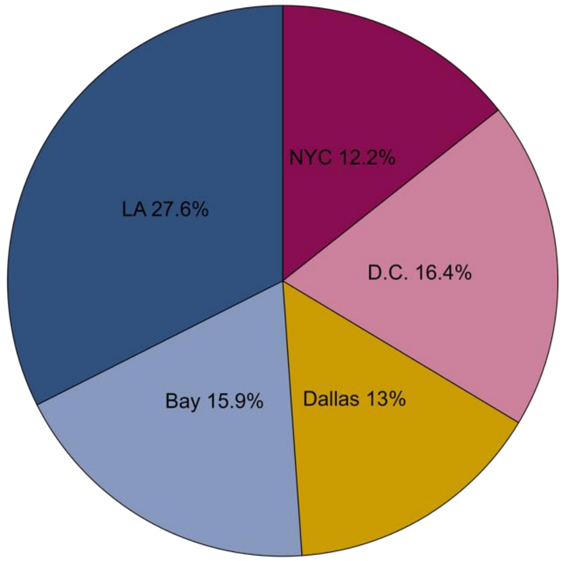
This table reports results of the baseline regression for different groups of leases. The cross-sectional model we estimate is below.

$$S_i = \sum_{t=s_i+1}^{e_i} R_t + \beta_A(T_i \times A_i) + \sum_{p=1}^{P} \beta_p\left(T_i \times X_i^p\right) + \sum_{t=s_i+1}^{e_i} \varepsilon_{i,t}$$

In this model, the dependent variable S_i is the sum of the monthly rents (per square foot) for the entire lease term duration of the lease i, s_i is the month at the end of which the lease i commences, and e_i is the month at the end of which the lease expires, R_t is the coefficient of month dummies, T_i is the lease term in months, A_i is lease Abundance that is calculated based on both lease size and lease term, X_i^p for $p = 1, \cdots, P$ are control variables, including continuous variables - lease size (log square feet demeaned by market), lease term (log months demeaned by market), building size (log square feet demeaned by market) – and dummy variables for building age cohorts, submarkets, net leases, renewed leases, subleases, leases signed before commencement, leases with renew options, leases with free rents, leases with tenant improvement allowance, the tenant being a public firm, and the tenant being a single tenant. This table reports estimates of lease Abundance only. The stars ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

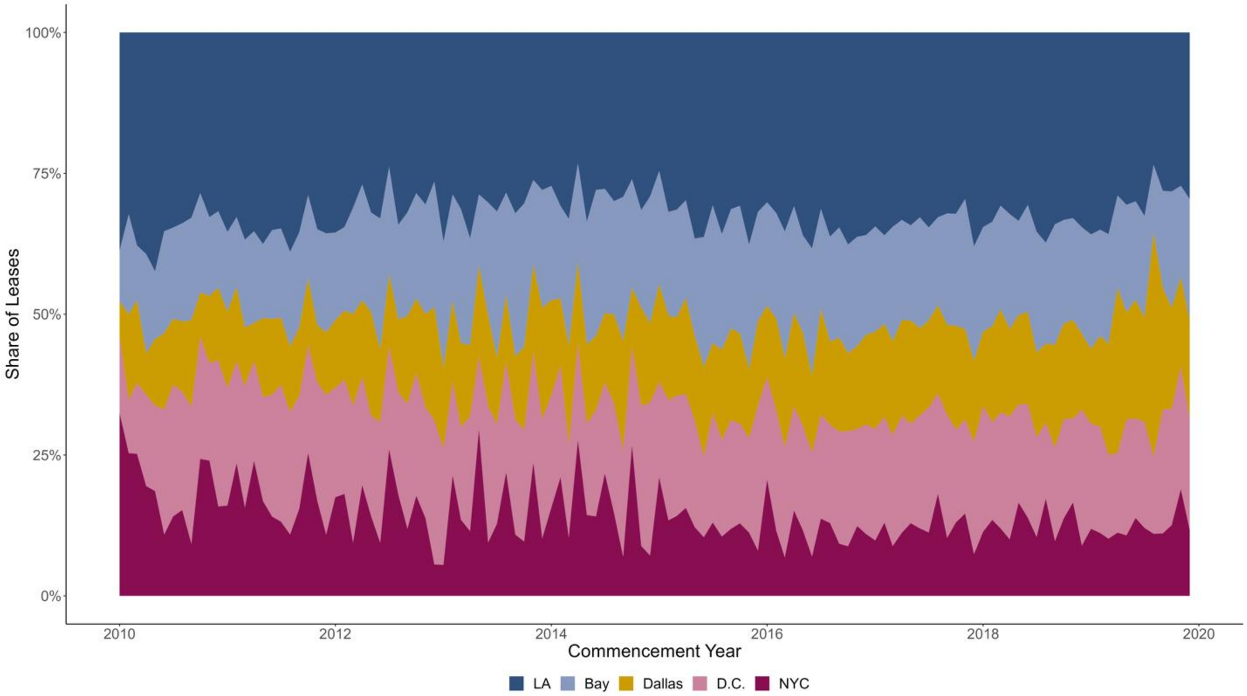
	Panel A: by lease size		
	Small leases	Medium leases	Large leases
Abundance	0.007	0.018**	0.038**
	(0.009)	(0.008)	(0.016)
	Panel B: by lease terms		
	Short leases	Medium leases	Long leases
Abundance	0.059***	0.020***	0.064***
	(0.013)	(0.006)	(0.011)
	Panel C: by building size		
	Small buildings	Medium buildings	Large buildings
Abundance	0.004	0.018**	0.054***
	(0.014)	(0.009)	(0.007)

Figure 1. Number of Class A Office Lease by Market



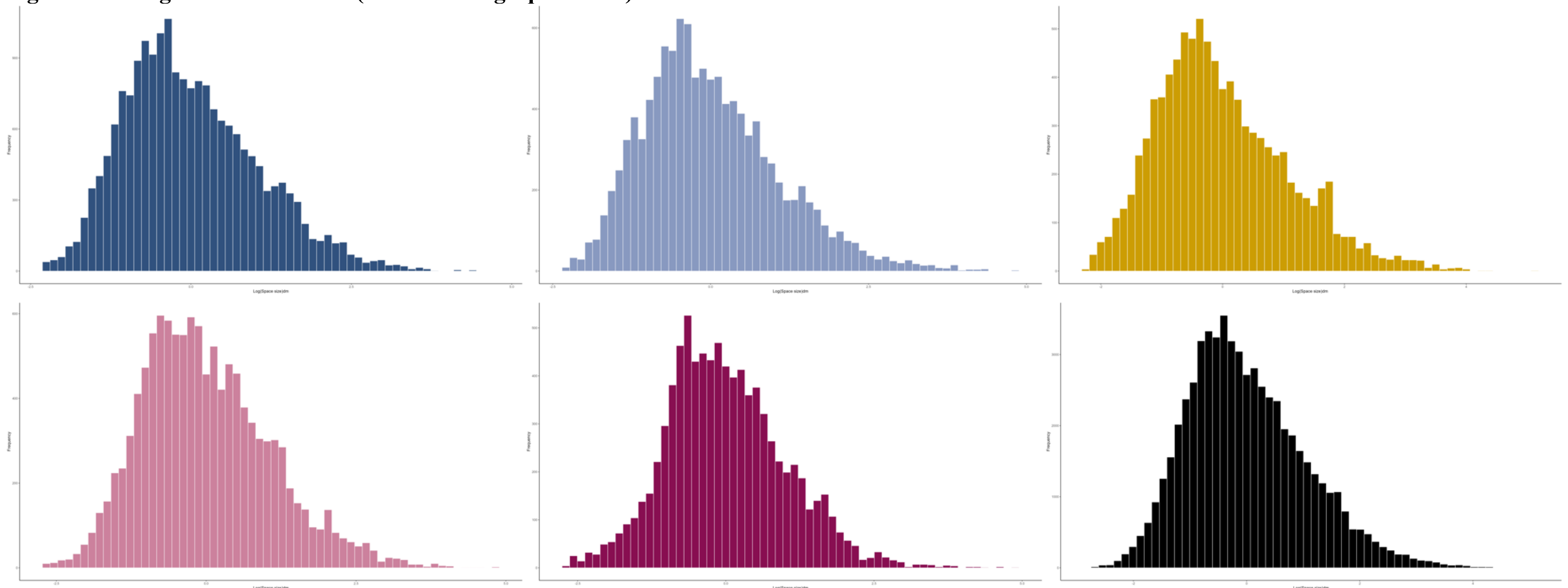
This figure shows the percentage share of leases by market out of all class A office leases in the sample commenced from January 2010 to December 2019 in five US markets.

Figure 2. Number of leases by location over time



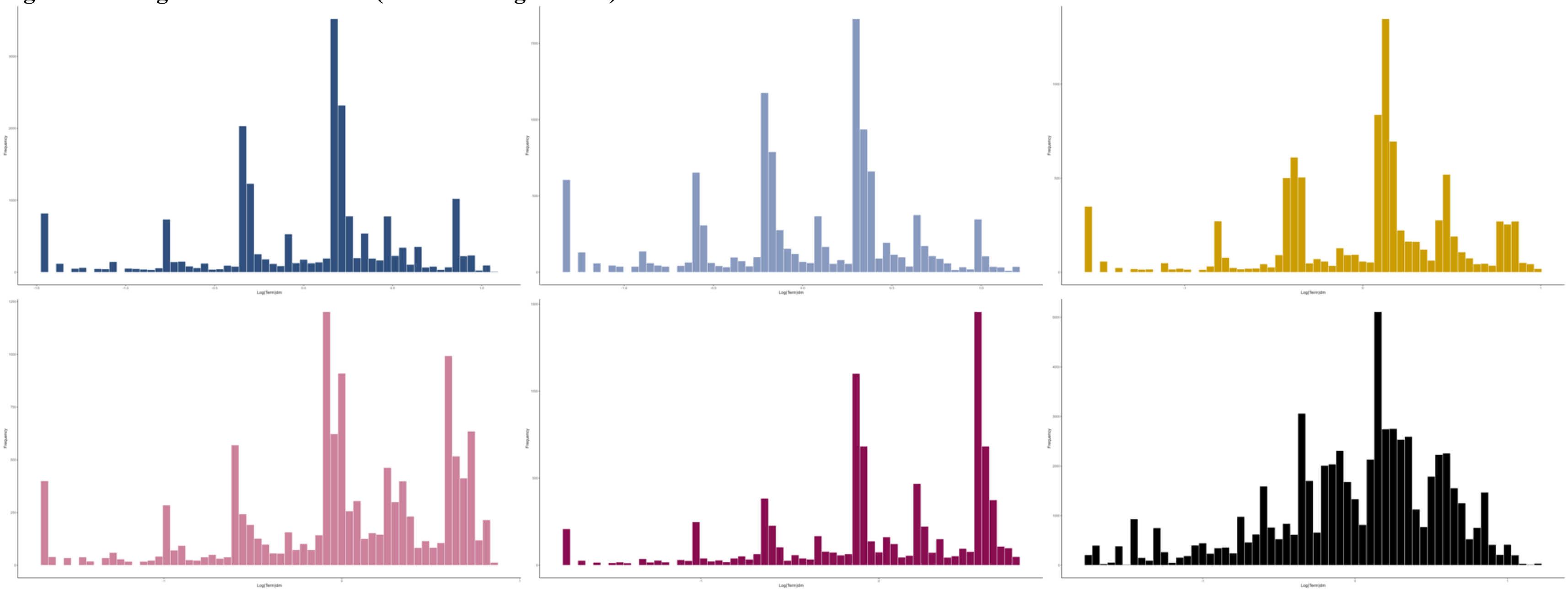
This figure shows the percentage share of leases by geographical locations out of all leases commenced in each year in the sample of class A office leases from January 2010 to December 2019 in five US markets.

Figure 3. Histograms of lease size (demeaned log square feet)



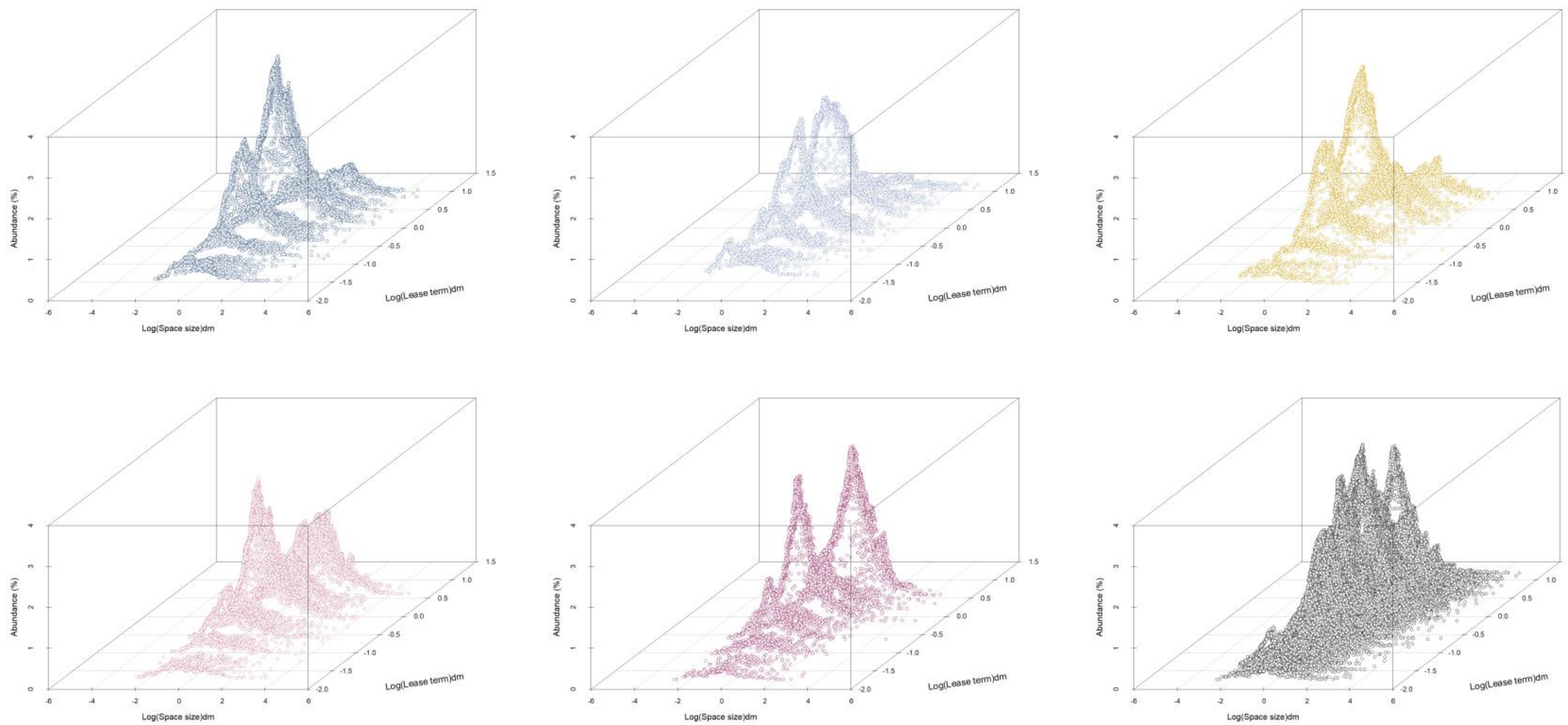
This figure shows the histograms of lease size (demeaned log square feet) for LA, Bay, Dallas, DC, NYC, and the whole sample respectively.

Figure 4. Histograms of lease terms (demeaned log months)



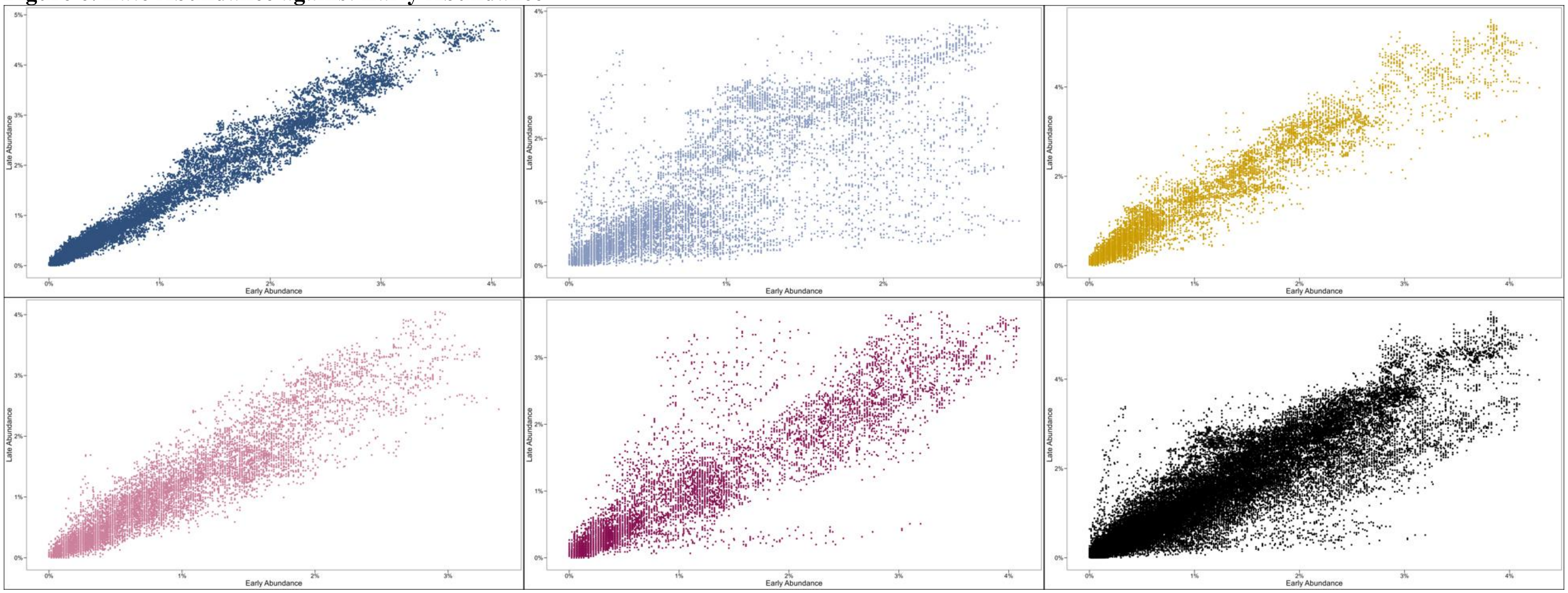
This figure shows the histograms of lease terms (demeaned log months) for LA, Bay, Dallas, DC, NYC, and the whole sample respectively.

Figure 5. Abundance against size and terms



This figure shows the three-dimensional relationship between lease Abundance, lease size, and lease term in each of the five markets and the whole sample. A lease's Abundance equals the percentage share of leases in the same market with similar (+/-0.1) space size and similar lease terms. Log(Space size)dm is the logarithmic value of lease space size demeaned within each market. Log(Term)dm is the logarithmic value of lease term demeaned within each market. The graphs are for LA, Bay, Dallas, DC, NYC, and the whole sample respectively.

Figure 6. Late Abundance against Early Abundance



This figure plots each lease's Late Abundance against its Early Abundance in each market and the whole sample. We calculate Early Abundance for a lease by dividing the number of similar leases that commenced before January 2015 by the total number of leases in the same period. Similarly, we calculate Late Abundance for a lease by dividing the number of similar leases that commenced in and after January 2015 by the total number of leases in the that period. The graphs are for LA, Bay, Dallas, DC, NYC, and the whole sample respectively.