Institutional Landlords in Industrial Real Estate Markets*

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January 2026

ABSTRACT

Motivated by the rapid growth of institutional investors in the industrial real estate market, we study their investment strategy and its implications for the leasing market. We first document that institutional investors tend to geographically cluster their properties and argue that this strategy mitigates large firms' hold-up problems in the leasing market. Using comprehensive U.S. lease transaction data, we find supporting evidence for the hold-up problem in the industrial real estate market: large firms prefer renting from large property owners and in areas with concentrated property ownership, but experience higher rents in sequential bargaining. Consistent with the role of institutional property owners in the hold-up problems, large firms pay lower rents to institutional owners, especially those with more clustered holdings. We further provide causal evidence by exploiting large institutional mergers as plausibly exogenous shocks to local ownership clustering.

JEL classifications: G23, L14, R33.

Keywords: institutional investors, industrial real estate, rent, hold-up problem.

*We thank Sanjiv Das, Sameul Lee, Zhuoran Lu, Wenjian Xu, and all other seminar participants at Cornell University, Santa Clara University, and Central University of Finance and Economics. All errors are our own.

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1. Introduction

U.S. firms incur substantial expenditures on industrial real estate, and leasing represents a principal method of employing industrial real estate properties. For instance, Ghent, Torous and Valkanov (2019) find that nonresidential properties accounted for almost 30% of the assets of U.S. non-financial firms as of 2017, and Li and Yu (2023) find that capitalized rental expense accounts for roughly 20% of physical productive assets among U.S. public firms.[1] One major change in the industrial real estate market in recent years is the growing ownership of institutional landlords (WSJ, 2022; Business Insider, 2024). The growing ownership of institutional landlords raises a natural but important question: how does institutional landlords' ownership affect the rental cost of industrial real estate properties?

This paper finds that institutional landlords tend to invest in geographically clustered industrial real estate properties, and that the increasing institutional ownership lowered the rent for large firms. By industrial restate properties, we mean production sites such as warehouses, distribution centers, logistics facilities, manufacturing sites, and flex spaces. Within an area, sites that are close in distance are often complementary to each other in industrial productions, especially for large firms. When a firm rents a site, the productivity of this site often depends on whether the firm is able to rent other nearby sites. As a result, a firm renting multiple sites in principle faces a hold-up problem: after the firm rents a site, the landlord can hold the firm up by asking for a higher rent for the complementary sites. We show evidence that the institutional landlords – via their ownership of geographically concentrated sites – mitigate the hold-up problem and thus lower the rent for large firms.

Over the past 20 years, institutional landlords' ownership in industrial real estate grew significantly. By institutional landlords, we mean banks, investment management companies, insurance companies, private equity funds, pension funds, and other funds. Ghent et al. (2019) provide a comprehensive survey that illustrates the importance of industrial real estate

[1] Li and Yu (2023) capitalize rental expense (XRENT) from operating leases and refer to this capitalized item as leased capital. Overall productive assets are the sum of leased capital and purchased tangible capital as measured by Property, Plant, and Equipment-Total (Net), that is, PPENT.

as an asset class for these entities and also discusses their ownership patterns over time. The fact that PE funds, including Bain Capital, KKR, and Blackstone, have been extensively purchasing industrial real estate properties has been widely covered by the media (see WSJ (2022); Business Insider (2024)). Our own estimate suggests that institutional landlords' ownership in terms of the square footage increased steadily from roughly 5–6% in the early 2000s to more than 12% by 2022.

We find that institutional landlords tend to hold tightly clustered properties in small geographical areas relative to non-institutional owners. Using data on the full stock of U.S. industrial real estate properties and their owners (i.e., CoStar and Real Capital Analytics), as well as the lease transactions (i.e., Compstak), we find that if a property's landlord is institutional, then on average 20.8% of that landlord's other properties are located in the same MSA, compared to 14.1% if the property's landlord is not institutional. We also find that properties located within spatial clusters are more likely to be purchased by institutional investors. If the property is located within a geographical cluster of properties, the property's buyer is 5.9% more likely to be an institutional investor. The increasing institutional ownership leads to more geographically proximate properties owned by one or a few landlords, which we refer to as "ownership clustering."

As institutional landlords increase ownership clustering, the hold-up problem arising from the complementarity of geographically proximate properties within an area could in principle be alleviated. To formalize the hold-up problem, consider the following example. Suppose that due to operational need, a firm considers renting two sites in an area. Two sites are complementary – without the second site, the first site cannot run at full capacity. [2] The two sites are owned by two different landlords. After the firm leased the first site from landlord A and committed to pay the rent, landlord B can charge a higher rent for the second site than its regular rent. In other words, leasing the first site is a relationship-specific investment to

[2] For instance, a retailer might rent several regional warehouses nearby to streamline distribution channels; an electronics company might rent a manufacturing plant to assemble products, along with a separate warehouse nearby to store finished goods; a pharmaceutical company could have its R&D laboratory close to its manufacturing plant which allows for rapid testing and quick scaling of production of new drugs.

landlord B, because the lease is more valuable within the relationship with him than outside it. As a result, landlord B can hold the firm up and extract surplus via charging a higher rent (Grossman and Hart, 1986; Hart and Moore, 1990; Buchanan and Yoon, 2000).

We document three facts that are consistent with the hold-up problem. Although it in principle arises as long as multiple sites within an area are complementary, we conjecture that the hold-up problem is more pronounced for large firms, which are more likely to operate multiple sites. First, we find that large firms indeed have a preference to rent adjacent properties, suggesting that adjacent properties within an area are complementary to each other in a large firm's industrial production. We find that the average observed distance between two properties of a large firm is approximately just 5.9 miles. This distance is smaller than the average distance between two otherwise similar properties of small firms, which is 15.7 miles. The complementarity of adjacent properties could potentially give rise to the hold-up problem. Second, we find that large firms experience higher rent in subsequent leases when they engage in sequential bargaining with multiple landlords. Third, we find that large firms tend to rent from large property owners, who own many sites. This avoids sequentially bargaining with multiple property owners and alleviates the hold-up problem.

As institutional landlords increase ownership clustering, that is, concentrate property ownership geographically, the hold-up problem should in principle be alleviated. Thus, the increasing institutional ownership in the industrial real estate market should decrease the rent for tenants on average. To test this hypothesis, we compile a comprehensive dataset on U.S. industrial real estate properties and lease transactions from 2001 to 2022. We use data on lease prices, tenants, landlords, and other contractual terms from 186,890 distinct industrial lease contracts. This data comes from CompStak, a proprietary platform in which commercial real estate brokers exchange information on executed leases. To accurately measure institutional ownership, we also link the leases to property-level data on ownership and landlord dynamics from CoStar and Real Capital Analytics (RCA), and reconcile the inconsistencies in these databases. Using this comprehensive dataset and fixed effect regressions, we find that institutional landlords indeed appear to charge rents that are 0.46–1.34 dollars per square foot per month lower on average compared to non-institutional landlords.

We show that the fact that institutional landlords appear to charge lower rents is driven by the fact that ownership clustering reduces the rent of large tenants. Specifically, we classify a tenant as large if it hires more than 150 employees, which is the 75th percentile of the employment size distribution. We also define a county that has more than five actively-leased properties to form a geographical cluster of properties. Using fixed effect regressions, we find that when a large tenant rents a property from an institutional landlord and the property is located in a geographical cluster of properties, the rent is 0.79 – 0.85 dollar per square foot per month lower (7% of the average rent). Note that when a large tenant rents a property from an institutional landlord but the property is located among a geographically dispersed set of properties, the rent is, however, not significantly different from that charged by non-institutional landlords. Alternative explanations, such as institutional landlords providing lower-quality services, are difficult to be consistent with these results. Our regression controls for a rich set of features on property quality and characteristics, as well as tenant and county-year fixed effects, and the results are also robust to different classifications of large tenants.

Besides, if complementary properties are subject to hold-up problems, these properties will be under-utilized. See the model of Buchanan and Yoon (2000) for this prediction. We find that properties owned by institutional landlords tend to have higher occupancy rates compared to otherwise similar properties. Specifically, using property-level cash flow and operating data from Trepp, we find that properties owned by institutional landlords are 4.4% more likely to be fully occupied than properties owned by non-institutional landlords but are similar in features including property age, size, distance to market center, and quality, etc. This finding is consistent with institutional landlords mitigating the hold-up problem and increasing the utilization rate of industrial real estate properties.

We are interested in the effect of ownership clustering caused by institutional landlords on rent. A key endogeneity concern for the fixed effect regressions is that institutional ownership may affect rent through other channels. For example, properties owned by institutional landlords may be of lower quality; thus, the rent is lower, yet quality is not fully unobservable. To mitigate the endogeneity concern, we exploit three mergers of private equity funds that occurred in three distinct time periods. In these mergers, the acquirers purchased all the properties from the targets with no selections, and in certain local areas, this increased ownership clustering. The increase in ownership clustering is plausibly exogenous to property quality and local market conditions.

We utilize difference-in-differences regressions to identify the effect of private equity mergers. We restrict the sample to lease contracts signed by large tenants. We classify a property as being treated if it is located in a county in which the acquirer purchases one or more properties from the target in the merger. A property is classified into the control group if it is located in such a county but is owned neither by the target nor by the acquirer, or if it is located in a county not affected by the merger. We verify that rents in the treated and control groups were not significantly different during the six-month period before the merger. During the 18-month period after the merger, the rent of treated properties declined by roughly 4.2 dollars per square foot per month. This suggests that ownership clustering caused by institutional landlords indeed lowered the rent for large tenants.

The rest of the paper is organized as follows. In Section 2, we provide a literature review. In Section 3, we introduce the data on industrial real estate leases and properties used in our analysis. In Section 4, we show evidence that the increasing ownership of institutional landlords lowered the rent for large tenants, consistent with ownership clustering mitigating hold-up problems in the industrial real estate market. Section 5 conludes.

2. Literature Review

We contribute to the literature on the role of institutional investors in the real estate market. Austin (2022) and Gurun, Wu, Xiao and Xiao (2022) find that institutional ownership led to higher prices and rents of residential real estate and, meanwhile, increased neighborhood diversity and safety. Lambie-Hanson, Li and Slonkosky (2019) find that the increase in institutional ownership contributed to 9 percent of the increase in single-family residential property prices from 2007 to 2014. These papers studied the residential real estate market, and our focus is instead on the industrial real estate market. We find that the increasing institutional ownership lowered the rent of industrial real estate properties for large tenants. Related to us, Cvijanovic, Milcheva and Van de Minne (2021) find that higher institutional ownership is followed by more volatile commercial real estate prices.

The literature has shown that institutional landlords have different preferences for properties than other landlords. Ghent (2021) finds that delegated investors concentrate investments in cities with higher transaction turnover and prefer tenants that are publicly listed firms since the rent cash flow risk is similar to that of a corporate bond. Cvijanović, Milcheva and Van de Minne (2022) find that the probability that a large (small) seller will sell a property to a similar-sized buyer is higher, keeping all else equal. Compared to them, our new finding is that institutional investors have a preference for geographically clustered industrial real estate properties. This preference has new predictions on institutional landlords' impact on this market.

The literature has well studied the hold-up (hold-out) problem in real estate development and coined it as the "land assembly problem": land assembly projects are frequently delayed or blocked by holdout landowners attempting to capture a greater share of the gains from trade, leading to fragmented and inefficient land use. In general, attempts to assemble complementary goods or resources with fragmented ownership – providing multiple parties the right to exclude – are subject to the hold-out problem sometimes referred to as the "tragedy of the anticommons" (see Michelman (1967); Heller (1998); Buchanan and Yoon (2000); Parisi, Schulz and Depoorter (2005) and Grossman, Pincus, Shapiro and Yengin (2019)). The model of Buchanan and Yoon (2000) predicts that if a resource is subject to the tragedy of anticommons, the price of the resource will exceed the competitive price, and the resource will be under-utilized. Our contribution is to provide evidence that institutional landlords mitigate the hold-up problem in the industrial real estate market via concentrating the property ownership geographically.

3. Data

We study U.S. commercial real estate in the industrial sector from 2001 to 2022. Following standard industry and academic practice, we define industrial real estate as properties used for warehousing, distribution, logistics, manufacturing, and flex space.[3] Our main analysis relies on two types of data:(i) contract-level rental data that provide granular information on lease pricing and tenant characteristics, and(ii) detailed property-level information that allows us to track landlord ownership, spatial structure, and market exposure over time.

3.1. Sample construction

Our lease-level data come from CompStak, a proprietary platform in which commercial real estate brokers share information on executed leases in exchange for access to comparable transactions. We use CompStak data covering U.S. industrial leases executed between January 2001 and December 2022.[4]The CompStak data provide rich information on the lease, the building, and the tenant. Lease-level variables include execution date, lease term, rent information, lease size in square feet, and lease type (e.g., new lease, extension, or expansion). Building characteristics include street address, building class (A, B, or C), the year the property was built. Tenant information includes tenant name, number of employees, and

[3]Industrial properties in our sample are predominantly warehouses, which account for 55.3% of all properties. Manufacturing facilities and distribution centers represent 16.3% and 15.4% of the sample, respectively. The remaining properties fall into smaller industrial categories. A flex building is a hybrid industrial property designed to accommodate both light industrial use and office use within the same structure.

[4]The data originate from brokers' deal files and reflect transactions negotiated by participating agents rather than a designed random sample of all leases. As a result, the CompStak sample is not intended to be fully representative of all commercial real estate contracts in a given market. Nevertheless, CompStak is the leading source of granular lease-level information in U.S. commercial real estate and is widely used in both academic and industry research.(Liu, Rosenthal and Strange, 2018; Gupta, Mittal and Van Nieuwerburgh, 2022; Rosenthal, Strange and Urrego, 2022; Brueckner and Rosenthal, 2025)

ticker symbol for publicly traded firms. These variables allow us to track lease pricing and contract characteristics at a highly disaggregated level.

While CompStak provides rich lease-level information, it does not record changes in property ownership following lease execution and therefore cannot be used on its own to track landlord characteristics dynamically.[5] To characterize landlord identity and their geographic footprint, we require detailed information on property owners and how ownership changes over time. We supplement the lease data with property- and transaction-level information from CoStar and Real Capital Analytics (RCA), which allows us to assign each lease to the relevant property owner and to follow ownership changes over time.

Our underlying property universe comes from CoStar, which provides comprehensive building-level coverage of U.S. industrial real estate, including street address, geographic coordinates, rentable building area, and year built. This property file serves as the backbone, as it includes both transacted and non-transacted properties and provides the spatial information needed to measure landlords' geographic footprints and clustering patterns. However, CoStar's property file is cross-sectional and does not record changes in ownership over time.

We supplement the CoStar property universe with transaction data from Real Capital Analytics (RCA) and CoStar. These transaction records allow us to observe when properties change hands and to identify the associated buyers and sellers. RCA is widely regarded as the industry benchmark for ownership information because it standardizes buyer and seller names and devotes substantial resources to identifying the ultimate beneficial owner behind each transaction. RCA also classifies market participants into detailed investor types, which enables us to distinguish among different categories of institutional and non-institutional owners. However, RCA only covers properties that have historically sold for more than $2.5 million, excluding many smaller industrial assets.[6]

To capture ownership changes for smaller properties and transactions below RCA's cov-

[5] CompStak records only the contemporaneous landlord associated with a lease at the time the record is created under "current landlord" and does not track subsequent changes in ownership.

[6] Ghent (2021) provides a detailed discussion about the advantage of RCA data, and the detailed investor types in RCA.

erage threshold, we complement RCA with CoStar transaction data, which provide broader coverage of the market. While CoStar transactions are more comprehensive, their ownership and buyer–seller fields are often noisy and inconsistently recorded, particularly for institutional investors. We merge RCA and CoStar transaction records to obtain both broad coverage and reliable ownership classification. We do so by matching transactions across the two sources using property address and transaction date, and by applying fuzzy name matching to link buyer and seller names where exact matches are unavailable. This combined transaction dataset allows us to track ownership changes across the full property universe while extending RCA's standardized owner name and investor type classification to transactions recorded only in CoStar.

We link the lease-level data from CompStak to the property-level ownership panel using a multi-step matching procedure at the property level. The goal of this procedure is to assign each lease to one or more properties in the CoStar universe and to inherit the corresponding ownership histories from the merged RCA–CoStar transaction data. Each lease is first matched to a CoStar property based on standardized street addresses and geographic coordinates.[7]When address information is incomplete or ambiguous, we further restrict potential matches using building characteristics, including rentable building area and year built. Using this procedure, we successfully match approximately 82% of industrial lease contracts in CompStak to at least one CoStar property. The final contract-level sample consists of 186,890 distinct industrial lease contracts.[8]

Throughout the analysis, we focus on net effective rent (NER), the standard pricing measure in the commercial real estate industry. NER augments the contractual rent schedule,

[7]Address standardization is implemented using the Google Maps API, which harmonizes street names and returns latitude and longitude coordinates when available.

[8]CompStak and CoStar rely on different address aggregation methods, lease contracts and properties cannot always be matched one-to-one. For example, a single lease contract may cover multiple properties, and a single transaction may involve multiple assets. To preserve observations for the empirical analysis, a lease contract may be matched to more than one CoStar property. Among these contracts, 86.3% are matched to a single CoStar property, and 91.5% are matched to no more than two properties. Property-level characteristics are aggregated to the contract level using either equal weights or weights proportional to rentable building area (RBA), reflecting the relative likelihood that a lease is associated with each matched property.

which specifies a nominal rent for each month of the lease, by incorporating rent concessions such as free-rent periods and landlord-provided tenant improvements. (Gupta et al., 2022) By converting all cash and in-kind transfers between landlords and tenants into a common monthly rent equivalent, NER reflects the average rent earned by the landlord over the lease term. Using NER allows us to measure the true economic price of space faced by tenants and received by landlords, rather than relying on nominal contract rents that omit important non-price components of commercial lease contracts.

Large tenants play a distinct role in industrial real estate markets. These tenants typically operate at scale, occupy multiple facilities within the same market, and make location decisions that are tightly linked to logistics networks, distribution hubs, and supply-chain efficiency. As a result, they often face substantial relocation costs and exhibit longer planning horizons than smaller, local tenants. We define large tenants based on tenant employment size. Specifically, we construct the employment size distribution using all tenants in the matched CompStak sample for which employment information is available and classify a tenant as large if its employment exceeds the 75th percentile of this distribution. This threshold corresponds to firms with more than approximately 150 employees. Under U.S. Census definitions, firms with more than 500 employees are classified as large and firms with fewer than 20 employees as small; our measure therefore captures medium-to-large tenants rather than small local firms.

By contrast, landlord scale and clustering are inherently local concepts that depend on a landlord's footprint within a given market, and are therefore measured using market-specific ownership shares and property counts. We define a landlord as large if the landlord's active rented area in the county exceeds the 75th percentile in that county–month pair. We also provide a detailed variable description for all the control variables we use for analysis in Table A.1.

3.2. *Institutional investors*

We define institutional investors based on the investor-type classifications provided by RCA, which distinguish institutional owners from private and owner-operator investors based on organizational form and investment mandate. RCA classifies buyers and sellers into broad categories such as institutional, private, and public, with finer distinctions within each group. The institutional category includes banks (BANK), investment managers (INVM), private equity funds (PEFU), pension funds (PENS), finance companies (FIN), insurance companies (INS), sovereign wealth funds (SWF), and open-end funds (OPENS). We treat real estate investment trusts (REITs) separately from other institutional investors because they operate under distinct regulatory and tax regimes. They tend to hold assets over longer horizons and adjust their portfolios less frequently than private institutional investors.[9] These features may limit their ability or incentive to pursue opportunistic, locally concentrated acquisition strategies, even when such strategies could generate short-run scale economies.

Figure 1 provides the shares of transaction volume by dollar value made by each category of investors at the national level aggregated across all years. Following Ghent (2021), we classify investors who make five or fewer purchases over the entire sample period as SMALL, considering the difficulty of reliably identifying such infrequent participants. These small buyers account for approximately 20% of transaction volume. Figure 1 Panel A and Panel B show that institutional investors account for a substantially larger share of buyers than sellers, while small and owner-operator investors account for a disproportionately large share of sellers. This pattern indicates that institutional expansion in the industrial sector primarily occurs through acquisitions from smaller, less active owners, rather than through asset reallocation among large institutional players.

Figure 2 illustrates the evolution of institutional ownership in the U.S. industrial real estate sector from 2001 to 2022, using the CoStar property universe combined with transaction-based ownership information from RCA and CoStar. Figure 2 Panel A reports the aggre-

[9] Mühlhofer (2019) also regards REIT holding period constraints as being binding.

gate share of properties owned by institutional investors. Institutional ownership increases steadily over the sample period, rising from roughly 5–6% in the early 2000s to more than 12%by 2022. The growth accelerates after 2015, consistent with a broader expansion of institutional capital into industrial real estate following the rise of e-commerce and logistics demand. This pattern highlights a substantial and sustained shift in ownership structure over time.

Figure 2 Panel B decomposes institutional ownership by investor type. Two groups account for the bulk of the increase: investment managers (INVM) and private equity funds (PEFU). Investment managers maintain the largest share throughout the period, while private equity ownership grows rapidly after the mid-2000s and again after 2016. Other institutional categories, such as pension funds, insurance companies, banks, and sovereign wealth funds, remain relatively small and stable in comparison. The two panels document that the growing presence of institutional investors in the industrial property market is driven by more active, professionally managed capital.

3.3. Additional data sources

We additionally use property-level cash flow and operating data from Trepp for a subset of properties that issued Commercial Mortgage-Backed Securities (CMBS) between 2001 and 2022. These data are used in Appendix B to examine operating expenditures, net operating income, debt service, and occupancy outcomes. Trepp provides standardized financial reporting for securitized commercial properties, including detailed cash flow and debt service statistics, allowing us to assess operating performance for properties with publicly available securitization histories. We match Trepp properties to our CoStar universe using property address, building characteristics, and issuance identifiers. The sample includes properties that issued Commercial Mortgage-Backed Securities (CMBS) at any time between 2001 and 2022, resulting in roughly 24,000 property–year observations.

3.4. *Summary statistics*

Table 1 provides summary statistics for the main datasets used in our analysis. Panel A, which serves as the primary sample for the empirical analysis, reports statistics for a matched contract-level dataset constructed from CompStak lease contracts and property-level information from CoStar. The average net effective rent is 11.26 (per square foot per month), with a median of 8.49, indicating a right-skewed rent distribution typical of industrial markets. The mean leased area is about 38,300 square feet, though the median is substantially smaller at roughly 11,900 square feet, indicating skewness toward large facilities. Approximately 21% of leases are signed with institutional landlords. On the tenant side, 22.6% of leases are signed by large tenants under the primary definition (top 75% of the employment distribution), corresponding to firms with more than roughly 150 employees. The share rises to 24.9% under the alternative 70th-percentile definition.

Panel B reports summary statistics for a matched property–year dataset combining CompStak tenant contract information with cash flow and operating characteristics from Trepp. This dataset is used to assess operating efficiency and financial performance at the property level.

Panel C reports summary statistics for a transaction-level dataset constructed from CoStar, which is used to analyze landlords' clustering and acquisition patterns. We further restrict transactions in which the buyer owns more than two properties, ensuring that clustering measures are economically meaningful. By using tenant contracts, property operating statistics, and property transactions as the units of observation, we are able to exploit variation in landlord scale, local ownership concentration, and operating performance at a highly disaggregated level.

4. Empirical Evidence

4.1. Evidence on hold-up problems

This section presents evidence on the presence of hold-up problems faced by large tenants. We investigate three testable predictions. First, large tenants should prefer leasing properties that are geographically adjacent, as spatial proximity reduces supply-chain coordination and operational costs. Second, if hold-up problems are economically meaningful, they should be reflected in rental pricing. In particular, large tenants should face higher rental costs when negotiating leases with multiple independent landlords. Third, because large landlords hold more extensive property portfolios and may be able to meet tenants' space requirements as a single counterparty, large tenants should sort into large or institutional landlords that internalize coordination across properties and can credibly commit to stable, long-term contracting. We empirically examine each of these predictions in turn.

First, we examine whether large tenants exhibit a preference for geographically adjacent industrial properties. A tenant is classified as large if its employment size exceeds the 75th percentile of this distribution, corresponding to firms with more than 150 employees.[10] Under U.S. Census definitions, firms with more than 500 employees are classified as large and firms with fewer than 20 employees as small. Our measure therefore captures medium-to-large tenants.[11]

To capture large tenants' preference regarding properties' adjacency, we measure the distances among their portfolio holdings. Given large tenants typically occupy more industrial properties relative to small tenants due to higher demand, the distance between their properties could be large relative to small tenants due to mechanical reasons. Therefore, in order to get a fair comparison, we construct a simulated benchmark that captures the spatial

[10] The employment size distribution is constructed using all tenants in the matched dataset for which employment information is available.

[11] In robustness checks, we also consider an alternative definition based on the 70th percentile of the employment distribution and find similar results.

distances expected under random portfolio formation within the same county and month.[12]

Our simulation method is as follows. Let K_{imt} denote the number of active contracts held by tenant i in county m during month t. For each event month, we compute the *real* distance measure as the mean pairwise distance among the locations of these K_{imt} contracts. To construct a counterfactual benchmark, we simulate random portfolios of size K_{imt} by sampling contracts from the pool of all active contracts in the same county–month.[13] We group observations by state, county, year, and month and collect the universe of active contracts and their geographic coordinates within each county–month. For each portfolio size $K \in \{2, \dots, 50\}$ such that the county–month contains at least K active contracts, we perform $B = 500$ Monte Carlo draws. In each draw, we sample K distinct contracts without replacement and compute the mean pairwise distance across their locations. This simulation allows us to compare the observed spatial configuration of large tenants' industrial portfolios to a counterfactual in which property locations are assigned randomly, holding the portfolio size fixed.

Table 2 presents a comparison between the observed spatial clustering of large tenants' portfolios and the simulated benchmark. Panel A reports the distribution of pairwise distances across properties within a tenant's portfolio for both the observed data and the simulated portfolios. For tenants holding two properties, the average observed distance between properties is approximately 5.888 miles, which is substantially smaller than the corresponding mean distance in the simulated portfolios. This pattern persists across different portfolio sizes and throughout the distribution of distances. Panel B reports t-tests comparing the observed and simulated distances at the mean as well as at the 25th, 50th, and 75th percentiles. Across all moments, the observed distances are significantly smaller than those generated

[12]We restrict attention to months in which a tenant signs at least one new contract. In non-event months, the set of active contracts is mechanically unchanged, so including such observations would duplicate the same spatial configuration without adding information.

[13]To ensure that the simulated benchmark reflects the broader local supply rather than the tenant's own footprint, we impose a market-thickness condition, where the total number of active contracts in county m and month t should be twice as many as K_{imt}. County–month cells that do not satisfy this condition are excluded, as random draws from such thin markets would disproportionately sample the tenant's own contracts and provide little meaningful variation.

by the simulation. Taken together, these results provide strong evidence that large tenants systematically cluster their industrial properties geographically, consistent with a preference for adjacent industrial portfolios.

Second, if hold-up problem exists, it should be reflected on rental price. Specifically, when a tenant signs with multiple landlords, the rental price should be higher compared to if she signs up with one landlord. If order to test the conjecture, we first define the indicator Multiple Landlords, which equals one if a tenant has simultaneously active leases associated with more than one landlord in the same county, including cases where landlord multiplicity arises either across leases or within a lease due to shared ownership, and zero otherwise. In Table 3, we examine how rental prices are associated with multiple landlords, while controlling for property size, age, contract lease term, contract lease term, distance to the market center, the number of rented areas owned by the landlord in the same county. All specifications include quality fixed effects and county-by-time fixed effects. I add it in the table as well. The analysis is based on the full sample of matched lease contracts. The results suggest that tenants face higher rents when they sign contracts with multiple landlords rather than one.

Third, given that hold-up problems impose a cost on tenants when they sign leasing contracts with multiple landlords (as suggested above), large tenants who are more likely to face hold-up problems should sort into large landlords. Specifically, we classify a landlord as large using either a local size-based measure, which is an indicator equal to one if the landlord's active rented space in a county–month exceeds the 75th percentile (Size75), or an institutional ownership indicator (INST). We then examine whether large tenants are more likely to be correlated with large tenants in Table 4. The results are consistent with our conjecture. As shown in the table, across all specifications, the coefficient on Large Tenant is positive and statistically significant, indicating that contracts signed by large tenants are more likely to be associated with large landlords. This pattern holds for both measures of landlord size and is robust to alternative definitions of large tenants. The magnitude of the estimates is similar across specifications, suggesting a stable association between tenant scale and landlord scale.

4.2. Institutional landlords' geographical clustering

As shown in Section 4.1, large tenants face hold-up problems when contracting with multiple landlords and may respond by sorting into large landlords who can satisfy their leasing needs through a single counterparty. Institutional investors, with their deep pockets, are a natural candidate to serve as such landlords. To meet the space and coordination needs of large tenants, institutional investors would need to hold multiple nearby properties, which implies a tendency toward geographic clustering in their industrial real estate portfolios. In this section, we investigate whether institutional investors geographically cluster their industrial properties.

To begin, we construct measures that capture the extent to which an owner's properties are geographically concentrated around a given property. Specifically, for each property, we compute the fraction of nearby properties owned by the same owner, where "nearness" is defined using fixed administrative boundaries such as counties, cities, or MSAs. These measures summarize the degree of local portfolio concentration within conventional market definitions. Using these boundary-based measures, Table 5 shows that institutional investors are more likely to hold properties in small, tightly clustered groups relative to non-institutional owners. This pattern is particularly pronounced for private equity owners(PEFU) and investment managers(INVM), who exhibit a stronger tendency to concentrate their properties within smaller geographic areas. [14]Although institutional investors own substantially more properties on average than non-institutional owners, their portfolios remain disproportionately concentrated at a local level. The fraction of properties clustered within a given region is significantly higher for institutional investors than for non-institutional owners.

[14]The analysis is based on a sample of 502,738 owners drawn from the CoStar universe. We restrict attention to owners who hold properties in more than one MSA. This restriction excludes highly localized owners—often operating on a single street and frequently recorded as single-purpose entities in the data. They are not directly comparable to institutional investors that operate across broader geographic areas.

Furthermore, to explore less restrictive clustering patterns that do not rely on fixed administrative boundaries. We use the Density-based spatial clustering of applications with noise algorithm (DBSCAN) with the haversine metric.[15] For each firm–year, the algorithm computes pairwise distances across all owned properties and assigns properties to a cluster if they lie within a specified neighborhood radius. We adopt a data-driven procedure to define this radius, setting it equal to the median nearest-neighbor distance computed from a 2% random sample of properties. We require a minimum cluster size of three properties for a firm–year observation to be classified as clustered. When constructing cluster-level measures, properties are weighted by rentable building area (RBA). Table B.1 examines the relationship between local clustering and institutional buyer participation in property transactions. The dependent variable is an indicator of the buyer's investor type. Columns (1)–(3) use an indicator for institutional ownership (INST) as the dependent variable, while Column (4) uses an indicator for private equity fund ownership (PEFU). The key explanatory variable is Cluster, an indicator equal to one if the property is part of a spatial cluster identified using the DBSCAN algorithm based on CoStar transaction data.

Across all specifications, the coefficient on Cluster is positive and statistically significant, indicating that properties located within spatial clusters are more likely to be purchased by institutional investors. The magnitude of the estimates increases when additional controls are included and remains stable across alternative specifications. Similar patterns obtain when private equity buyers are considered separately, suggesting that the association between clustering and institutional participation is not driven by a single ownership type. Taken together, the results in Internet Appendix Table B.1 document a strong association between spatial clustering and institutional investor participation in commercial real estate

[15]The formula is expressed as follows:

$$d_{ij} = 2 \times R \times \arcsin\left(\sqrt{\sin^2\left(\frac{\mathrm{lat}_i - \mathrm{lat}_j}{2}\right) + \cos(\mathrm{lat}_i) \times \cos(\mathrm{lat}_j) \times \sin^2\left(\frac{\mathrm{lon}_i - \mathrm{lon}_j}{2}\right)}\right),$$

where R represents the Earth's radius, a constant equal to 6,371 km. Here, $(\mathrm{lat}_i, \mathrm{lon}_i)$ denotes the latitude and longitude of property i.

transactions, consistent with institutional investors' tendency to acquire properties in close geographic proximity to their existing holdings.

4.3. Institutional landlords and rents

In this section, we examine the rental pricing of properties owned by institutional investors. Given their superior resources and scale, institutional investors may operate properties more efficiently, potentially allowing them to charge lower rents. We investigate whether institution-owned properties exhibit higher operating efficiency, whether they charge lower rents on average, and whether any resulting rent reductions are passed through to large tenants.

We begin with examining whether institutional investors differ from other owners in operating performance. Internet Appendix Table B.2 reports regressions of property-level cash flow and operating outcomes on an indicator for institutional ownership using CMBS-linked data from Trepp. Institutions-owned properties exhibit systematically better operating performance. Most notably, the coefficient on INST in the full-occupancy specification is positive and statistically significant, indicating that institutions-owned properties are more likely to be fully occupied, conditional on property characteristics and local market conditions. Institutional ownership is also associated with lower operating expenditures, higher net operating income, and lower debt service. Taken together, these patterns are indicative of higher operating efficiency among institutional investors. Combined with the evidence in Section 4.2 that institutional investors tend to acquire properties in close geographic proximity to their existing holdings, these results suggest that locally concentrated ownership may facilitate more effective property management and utilization.

Further, we examine whether institutions-owned industrial properties charge lower rental prices. Specifically, Table 6 studies the relation between institutional ownership and rents at the contract level. Across a wide range of specifications—including rich property and market controls and tenant fixed effects—rents are significantly lower for properties owned by institutional landlords. The negative and statistically significant coefficient on INST appears for both Winsorized Net Effective Rent and Net Effective Rent and remains stable when the sample is restricted to leases signed by large tenants. These results indicate that the cost efficiencies associated with institutional ownership are at least partially passed through to tenants in the form of lower rents, rather than being fully absorbed as higher margins.

Finally, If institutions mitigate hold-up problems faced by large tenants, this should be reflected in the drop of leasing price for large tenants. Table 7 explores how this rent pass-through varies with local ownership concentration, focusing on large tenants. The key coefficient of interest is the interaction between institutional ownership and local clustering (INST $\times$ Cluster). Across all specifications, this interaction term is negative and statistically significant, indicating that large tenants leasing from institutional landlords experience especially large rent reductions when those landlords operate in locally clustered markets. In contrast, the standalone INST coefficient is smaller in magnitude and statistically insignificant once clustering is accounted for, suggesting that the rent effects of institutional ownership are concentrated in markets where institutional investors hold a substantial local presence. Together, these results indicate that the pass-through of institutional investors' operating efficiencies is strongest for large tenants and in markets where institutional ownership is more geographically concentrated.

4.4. Identification

A key concern in interpreting the baseline rent results is that institutional investors do not enter local markets randomly. Their expansion decisions may reflect superior information or expectations about future local economic conditions, which could confound the relationship between institutional ownership and rents. In this case, observed rent differences may capture unobserved local demand shocks rather than operating efficiencies associated with institutional scale.

To isolate the scale economy channel from unobserved local economic conditions, we exploit plausibly exogenous variation in institutional ownership concentration induced by three large-scale mergers that occurred in distinct, non-overlapping time periods. These mergers mechanically alter landlord scale and market share across local markets based on pre-merger portfolio overlap, rather than contemporaneous market fundamentals or tenant–landlord matching decisions. Our identification strategy compares changes in rents across markets with different degrees of pre-merger overlap before and after merger completion. Under the assumption that, absent the merger, high- and low-overlap markets would have experienced similar rent trends, differential post-merger rent changes can be attributed to the merger-induced increase in institutional scale.

Table 8 reports details of the merger transactions. In these deals, acquirers typically purchase either all properties owned by the target or properties across several states, rather than selectively acquiring individual assets. Panel B and Panel C define treatment at both the market and property levels. At the market level, we classify counties as treated if the acquirer purchases one or more properties from the target in that county as part of the merger. Control counties are those in which either the acquirer or the target owned properties prior to the merger and did not experience any merger-induced transaction. This classification captures exogenous variation in local institutional ownership concentration driven by the merger.

At the property level, treated properties are those owned by the acquirer, whose local scale and market presence increase mechanically following the merger. We construct two complementary control groups. First, within treated counties, we use properties owned by landlords other than the acquirer or target as controls, which allows us to difference out local demand shocks common to all properties in the same market. Second, as a robustness exercise, we expand the control group to include properties located in control counties, where either the acquirer or the target had a pre-merger presence but that were not directly affected by the merger. This expansion increases statistical power and allows us to benchmark rent changes against markets with similar pre-merger exposure to the merging firms. Because treatment varies at the county–time level in this specification, we cannot include county-by-time fixed effects. Instead, we rely on msa-time fixed effects and property fixed effects to absorb common shocks and time-invariant heterogeneity.

Specifically, we use two different treatment variables: (1) $I(\Delta Properties > 0)$, a binary variable that equals one if the property i is located in the treated region and is owned by the acquirer prior to the merger; (2) $\ln(\Delta Properties{+}1)$, a continuous variable that is the number of properties gained from the merger in a given county.

$$rent_{ijt} = \alpha_0 + \alpha_1 Post_{ijt} + \alpha_2 Treated_{ijt} + \alpha_3 Treated_{ijt} \times Post_{ijt} + \beta X_{ijt} + \gamma_{j,t} + \gamma_i^p + \epsilon_{ijt} \quad (1)$$

$rent_{ijt}$ is the rent charged by contract i in county j at time t. To address concerns about unobservable characteristics that might influence both property selection by institutional investors and rental prices, we incorporate observable attributes such as property size, age, contract length, distance to the city center, and property quality into our analysis.[16] These factors are known to directly affect rental rates. Additionally, we include Property fixed effects (γ_i^p) to absorb time-invariant property characteristics, and County × year-month fixed effects ($\gamma_{county,t}$) to control for unobserved, time-varying factors at the county level that could impact the broader rental market.

Table 9 reports difference-in-differences estimates of the rent effects of merger-induced increases in institutional ownership concentration. The sample is restricted to leases signed by large tenants, defined based on tenant employment size. The dependent variables are Winsorized Net Effective Rent and Net Effective Rent. Columns (1) and (2) use a binary treatment indicator that equals one if a property is owned by the acquirer and located in a treated county—defined as a county experiencing a merger-induced increase in institutional ownership. Columns (3) and (4) instead use a continuous treatment measure defined

[16]Since not all properties are traded every year. In order to reduce the missing data in regressions, we use the building class information from the Compstak dataset to approximate the building quality. Class A is the highest, Class B is medium, and Class C is the lowest.

as $\ln(\Delta Properties{+}1)$, capturing the magnitude of the merger-induced increase in the acquirer's local footprint. Across all specifications, the coefficient on $Treat \times Post$ is negative and statistically significant, indicating that rents decline following merger completion for properties exposed to an increase in institutional ownership concentration. The results are robust across both rent definitions and treatment measures, and the magnitudes are economically meaningful.

All specifications include property fixed effects and county-by-time fixed effects, which absorb time-invariant property characteristics and common local demand shocks, respectively. As a result, identification comes from within-property changes over time and differential exposure to merger-induced institutional expansion across markets. Taken together, the difference-in-differences estimates provide causal evidence that merger-induced increases in institutional landlord scale lead to lower rents. Combined with earlier findings on operating efficiency and clustering, these results support the interpretation that cost efficiencies associated with institutional scale are passed through to large tenants following large-scale mergers.

To further assess the identifying assumptions underlying the difference-in-differences estimates in Table 9 and to examine the dynamic effects of merger-induced changes in institutional ownership, we conduct an event-study analysis around merger completion. Table 10 reports the estimated coefficients on event-time indicators for both Winsorized Net Effective Rent and Net Effective Rent, using the same sample of large-tenant leases and the same treatment definitions as in the baseline DiD specifications. In parallel, Figure 3 plots the corresponding event-study coefficients and confidence intervals.

The coefficients on the pre-merger interaction term (*Before* $\times$ *Treat*) are small in magnitude and statistically insignificant across all specifications, indicating no evidence of differential pre-trends between treated and control properties prior to the merger. This finding provides support for the parallel-trends assumption underlying the difference-in-differences design. In contrast, the post-merger coefficients ($After^1 \times Treat$, $After^2 \times Treat$, and $After^3$

$\times$ *Treat*) are negative and statistically significant, with the largest effects emerging in the first two post-merger periods and remaining economically meaningful thereafter. The dynamic pattern suggests that rent reductions materialize following merger completion and persist over time, consistent with gradual adjustments in contract terms rather than immediate price changes at the time of the transaction.

5. Conclusion

Within an area, properties that are close in distance are often complementary to each other in industrial production, especially for large firms. Leasing complementary properties from multiple owners tends to be subject to the hold-up problem: some owners attempt to capture a greater share of the gains from the lease, leading to higher prices and underutilization of the properties. We document facts that are consistent with the hold-up problem in the industrial real estate market.

In recent years, the institutional ownership of industrial real estate properties have grown significantly. We find that institutional landlords have a preference for geographically clustered industrial real estate properties. We show evidence that the institutional landlords – via their ownership of geographically concentrated sites – mitigate the hold-up problem and lower the rent for large firms.

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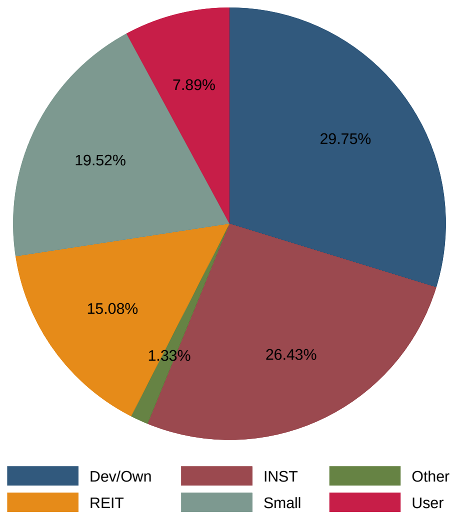
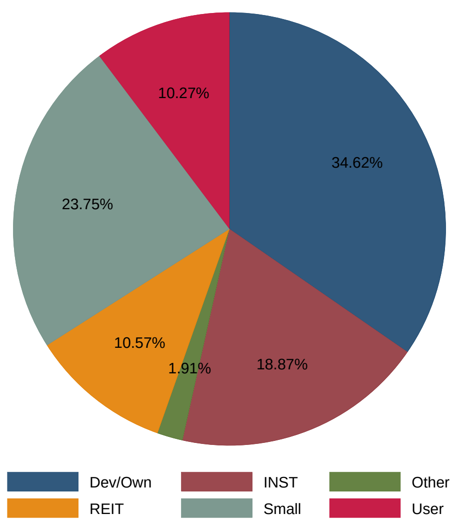
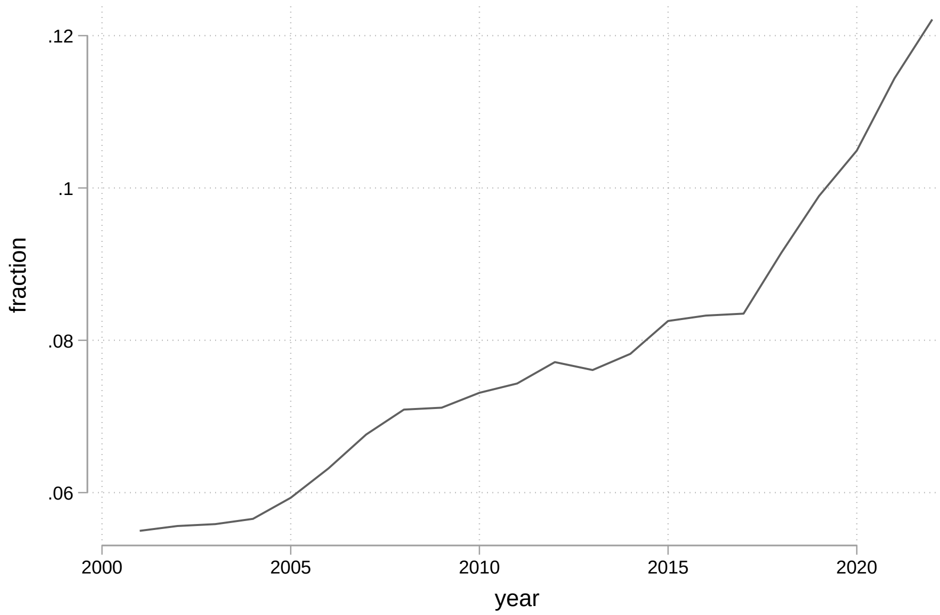


Panel A: Buyer composition

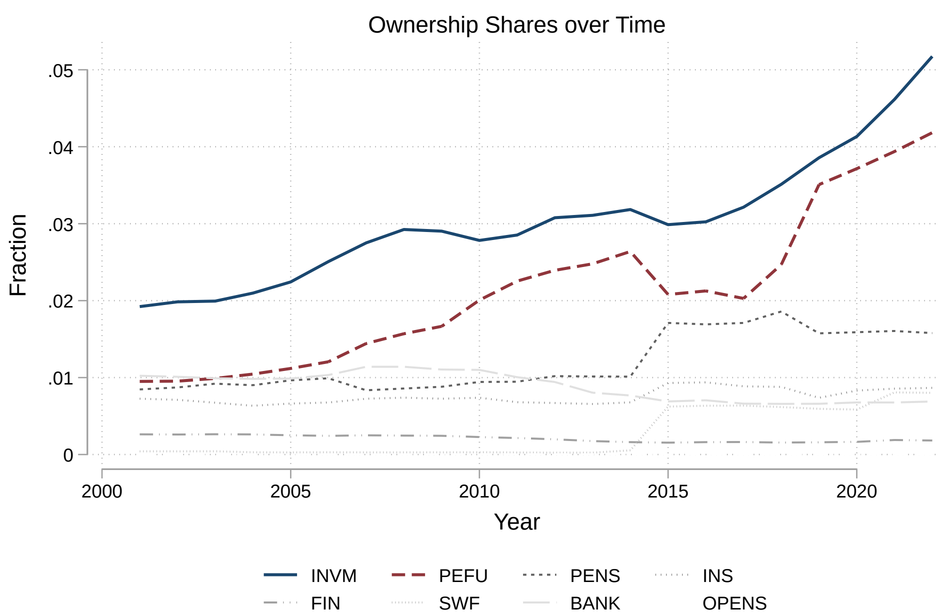


Panel B: Seller composition

Fig. 1. Investor composition in US industrial real estate, 2001–2022: Notes: (1) Dev/Own denotes developer/owner/operator, Inst Investor denotes institutional investors, including banks (BANK), investment managers (INVM), private equity funds (PEFU), pension funds (PENS), finance(FIN), insurance companies (INS), sovereign wealth funds (SWF), and open-end funds (OPENS). REIT denotes public and private REITs. User denotes corporations, government, and non-profit users. Other denotes other, and Small denotes a trader that makes fewer than five transactions over the full sample period. (2)Investor-type shares are averaged over 2001–2022 and are value-weighted. (3) Panel A is the buyer composition, and Panel B is the seller composition.



Panel A: Share of total institutional investors



Panel B: Share of institutional investors by type

Fig. 2. Share of institutional investor, 2001–2022. Notes: (1) Institutional investors are defined by RCA as including banks (BANK), investment managers (INVM), private equity funds (PEFU), pension funds (PENS), finance companies (FIN), insurance companies (INS), sovereign wealth funds (SWF), and open-end funds (OPENS). (2) Shares are weighted by RBA (rentable building area). (3) Panel A reports the aggregate share of institutional investors, and Panel B reports the composition by investor type.

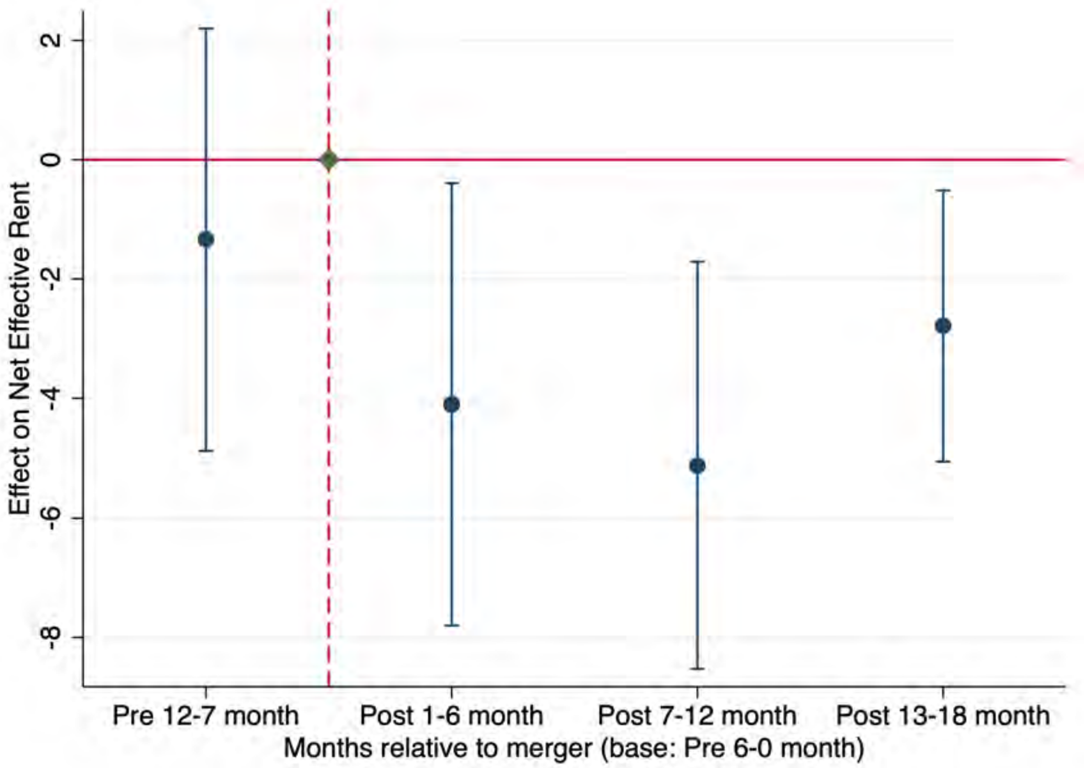


Fig. 3. Event Study of Rent Regression around Merger. This figure plots the estimated event-time effects of mergers on net effective rent based on Table 10 column 2. The sample consists of property–month contracts for properties located in counties affected by mergers. The horizontal axis reports event-time indicators defined as follows: Pre 12–7 corresponds to months -12 to -7 relative to the merger; the omitted base period (Pre 6–1) corresponds to months -6 to -1; Post 1–6, Post 7–12, and Post 13–18 correspond to months 1–6, 7–12, and 13–18 after the merger, respectively. The vertical axis reports the estimated coefficients on the interaction between treatment status and event-time indicators, with 95 percent confidence intervals.

Table 1
Summary Statistics

	Obs.	Mean	Median	Std. dev.	P25.	P75.
Panel A: CompStak Lease Contract-Level Variables						
Net effective rent	182859	11.255	8.490	10.784	5.710	12.770
Winsorized rent	182859	11.046	8.490	8.993	5.710	12.770
Age	186016	31.669	30	19.938	18	41
Lease term	183256	53.426	56	33.656	36	62
Transaction size (sqft)	186890	38299.320	11921	85233.670	4370	34337
Quality A	186890	0.193	0	0.394	0	0
Quality B	186890	0.548	1	0.498	0	1
Quality C	186890	0.229	0	0.420	0	0
Multiple Landlord	186890	0.116	0	0.320	0	0
Large Tenant (Large75)	186890	0.226	0	0.418	0	0
Large Tenant (Large70)	186890	0.249	0	0.433	0	0
Dist. to center (km)	186844	18.338	15.723	13.452	8.811	24.382
INST	186890	0.210	0	0.407	0	0
#props in same county	186890	11.865	2	24.212	1	10
#props in same MSA	186890	16.808	3	34.950	1	15
Large Landlord (Size75)	186890	0.482	0	0.500	0	1
Panel B: Trepp property-level statistics						
EXP	18599	0.247	0.241	0.150	0.142	0.345
NOI	18703	0.754	0.760	0.150	0.656	0.861
DS	18663	0.440	0.424	0.151	0.328	0.539
Full Occ	22638	0.761	1	0.426	1	1
INST	23893	0.275	0	0.446	0	1
age	23759	28.339	26	17.590	15	39
RBA	23893	151455	78177	204717	37467	180252
ln(app value)	23851	15.797	15.761	1.025	15.124	16.447
duration	23671	3.758	3	2.935	2	6
Dist. to center (km)	23884	19.077	15.648	14.944	8.953	24.726
#props in same county	23884	9.761	3	19.431	1	10
Panel C: Costar transaction-level statistics						
INST	176687	0.256	0	0.436	0	1
PEFU	148823	0.116	0	0.321	0	0
Cluster	176687	0.507	1	0.500	0	1
age	170336	31.819	30	20.472	18	42
RBA	176685	89446	37802	156614	15000	97287
Dist. to center (km)	176616	18.387	14.744	16.585	8.237	23.840

(continued) Summary Statistics

	Obs.	Mean	Median	Std. dev.	P25.	P75.
multi owner	176687	1.267	1	0.532	1	1
quality quartile	141752	2.695	3	1.099	2	4

Panel A is a matched tenant contract data from CompStak with property-level data from CoStar. All property-level statistics, including distance to center, INST, number of properties in the MSA or county, and large landlord status, are averages of properties related to each contract. This dataset is later used to estimate Tables 3, 4, 6, 7, 9, 10. Panel B is a matched property–year dataset combining tenant contract data from CompStak with cash flow statistics for properties that issued Commercial Mortgage-Backed Securities (CMBS) at any time between 2001 and 2022, based on Trepp data. All statistics are property–year averages following Trepp's property identifiers. This dataset is later used to estimate Table B.2. Panel C is a transaction-level dataset from CoStar that tracks all property transactions in which the buyer owns more than 2 property, making the Cluster variable meaningful. This dataset is later used to estimate Table B.1.

Table 2
Real and Simulated Spatial Dispersion of Large Tenants

Panel B. Real vs. Simulated Distances

	Real Distance				Simulated Distance			
K	Mean	p25	p50	p75	Mean	p25	p50	p75
1	5.888	0	0.372	7.264	15.670	11.011	15.114	20.071
2	7.738	0.237	3.604	12.270	16.242	11.604	15.743	20.505
3	9.092	1.285	6.263	14.857	16.785	11.586	16.439	21.170
4	10.577	5.107	6.072	18.046	17.383	10.703	17.101	25.343
Total	6.728	0	1.426	10.148	15.950	11.192	15.445	20.377

Panel A. Difference (Real – Simulated Distance), by K

K	Mean Δ	p25	p50	p75	N	t-stat	Sig.	Share($\Delta < 0$)
1	-9.782	-16.934	-11.209	-4.474	5376	-65.104	1%	0.857
2	-8.504	-14.863	-9.360	-2.735	1467	-33.232	1%	0.819
3	-7.692	-13.908	-7.461	-1.216	1090	-27.467	1%	0.790
4	-6.806	-7.154	-5.289	-3.574	118	-11.277	1%	0.941
Total	-9.223	-16.164	-10.370	-3.532	8051	-78.394	1%	0.842

Notes: This table compares the observed spatial clustering of large tenants' industrial portfolios to a simulated benchmark based on random assignment within each county–month. Observations are grouped into four bins based on portfolio size K: (1) $K = 2$; (2) $K = 3$; (3) K between 4 and 9; and (4) $K \geq 10$. These bins reflect meaningful variation in how dispersed larger vs. smaller multi-site portfolios can be within a market. Panel A reports the difference $\Delta = \text{Real} - \text{Simulated}$ and its distribution across tenant events. The simulated benchmark is based on 500 Monte Carlo draws for each market–time cell. "Share($\Delta < 0$)" indicates the fraction of cases in which real portfolios are more clustered than randomly drawn portfolios. The t-statistic reports a one-sided test of $H_0 : \mathbb{E}[\Delta] = 0$ against $H_1 : \mathbb{E}[\Delta] < 0$, with all K bins significant at the 1% level. Panel B summarizes the distribution of simulated and real distances separately. Across all portfolio sizes, real distances are substantially smaller than their simulated counterparts, indicating strong adjacency preferences among large tenants.

Table 3
Rent with Multiple Landlords

Dep var:	Winsorized Rent	Net Effective Rent	Winsorized Rent	Net Effective Rent
	(1)	(2)	(3)	(4)
Multiple Landlords	1.019***	1.059***	0.145**	0.197***
	(0.202)	(0.201)	(0.060)	(0.068)
ln(Age)	1.526***	1.632***	0.783***	0.811***
	(0.291)	(0.323)	(0.192)	(0.205)
ln(Size)	-1.943***	-2.031***	-1.528***	-1.649***
	(0.124)	(0.133)	(0.099)	(0.118)
ln(Dist. to Market)	0.299	0.317	0.282	0.330
	(0.587)	(0.638)	(0.316)	(0.361)
Lease Term	0.0459***	0.0499***	0.0321***	0.0353***
	(0.004)	(0.004)	(0.004)	(0.005)
ln(# of Props)	-0.363***	-0.369***	-0.225***	-0.231***
	(0.078)	(0.084)	(0.043)	(0.049)
Observations	164,515	164,515	63,824	63,824
Adjusted R^2	0.544	0.506	0.756	0.719
Quality FE	YES	YES	YES	YES
County × Time FE	YES	YES	YES	YES
Tenant FE	NO	NO	YES	YES
Cluster by Tenant	YES	YES	YES	YES

Notes: The dependent variables are Winsorized Net Effective Rent and Net Effective Rent at the contract level. The analysis is based on the full sample of matched lease contracts. Columns (1) and (2) report results for Winsorized Rent and Net Effective Rent without tenant fixed effects, while columns (3) and (4) report the corresponding specifications with tenant fixed effects. The indicator Multiple Landlords equals one if a tenant signs leases with more than one landlord in the same county, and zero otherwise. The set of control variables includes the rented area of the contract (ln(size)), property age (ln(age)), contract lease term, distance to the market center, and the number of rented areas owned by the landlord in the same county. All specifications include quality fixed effects and county-by-time fixed effects. Standard errors (in parentheses) are clustered at the tenant level. Statistical significance is denoted by $p < 0.01$, $p < 0.05$, and $p < 0.1$.

Table 4
Large Landlords and Large Tenants

	Large Tenant: Top 75%		Large Tenant: Top 70%	
	Size75	INST	Size75	INST
Large Tenant	0.0124***	0.0166***	0.0119***	0.0162***
	(0.003)	(0.003)	(0.003)	(0.003)
ln(Age)	0.0325***	0.0168***	0.0325***	0.0168***
	(0.006)	(0.006)	(0.006)	(0.006)
ln(Size)	0.112***	0.0255***	0.112***	0.0254***
	(0.004)	(0.005)	(0.004)	(0.005)
ln(Dist. to center)	-0.0154**	-0.0116	-0.0154**	-0.0116
	(0.006)	(0.010)	(0.006)	(0.010)
Lease Term	0.000105	0.000122	0.000106	0.000122*
	(0.000)	(0.000)	(0.000)	(0.000)
ln(#props in market)	0.191***	0.0900***	0.191***	0.0900***
	(0.005)	(0.008)	(0.005)	(0.008)
Observations	165,204	165,204	165,204	165,204
Adjusted R^2	0.516	0.175	0.516	0.175
Quality FE	YES	YES	YES	YES
County × Time FE	YES	YES	YES	YES
Cluster by County	YES	YES	YES	YES

Notes: The dependent variable a large landlords measure. Large landlords are measured either by a dummy variable for landlord above the 75th percentile of active rented space size (columns labeled *Size75*) or by an institutional ownership indicator (columns labeled *INST*). Large tenants are defined using alternative thresholds based on tenant employment size, corresponding to the top 75% or top 70% of tenants. The set of control variables includes the rented area of the contract (ln(Area)), property age (ln(Age)), lease term, distance to the market center, and the number of rented areas owned by the landlord in the same county. All specifications include quality fixed effects and county-by-time fixed effects. Standard errors (in parentheses) are clustered at the county level. Statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

Table 5
Summary Statistics of Clustering Patterns

	Non INST	INST	Diff (INST−Non)	INVM	PEFU
In the same MSA	0.141	0.208	0.067***	0.311	0.265
In the same city	0.098	0.126	0.027***	0.146	0.190
In the same county	0.122	0.166	0.044***	0.183	0.237
# properties	4.579	11.246		12.300	13.616

This table presents summary statistics on geographic clustering patterns from 2001–2022. All statistics are annual averages computed across all property owners. For each property-year observation, the clustering measure is the fraction of the owner's other properties located within the same geographic boundary (city, county, or MSA). The reported statistics are averages across all owners within each investor type. # properties reports the average portfolio size. Non INST and INST report averages for non-institutional and institutional investors, respectively. Column INVM and PEFU reports averages for investment managers (the largest institutional type) and private equity funds (the second-largest institutional type). Diff (INST−Non) reports the difference in means between institutional and non-institutional investors from two-sample t-tests. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6
Institutional Landlords and Rents

	Winsorized Rent			Net Effective Rent		
	Basic	Full Controls	Large Tenant	Basic	Full Controls	Large Tenant
INST	-1.344***	-0.462***	-0.663***	-1.387***	-0.522***	-0.797***
	(0.246)	(0.071)	(0.131)	(0.256)	(0.083)	(0.156)
ln(Age)		0.797***	1.060***		0.827***	1.150***
		(0.068)	(0.111)		(0.075)	(0.123)
ln(Size)		-1.513***	-1.642***		-1.633***	-1.807***
		(0.053)	(0.087)		(0.069)	(0.116)
ln(Dist. to Center)		0.280***	0.335***		0.328***	0.441***
		(0.075)	(0.119)		(0.089)	(0.138)
ln(#props in market)		-0.197***	-0.286***		-0.199***	-0.282***
		(0.025)	(0.048)		(0.029)	(0.055)
Lease Term		0.0321***	0.0381***		0.0353***	0.0425***
		(0.002)	(0.003)		(0.002)	(0.003)
Observations	169,622	63,824	22,114	169,622	63,824	22,114
Adjusted R^2	0.435	0.756	0.698	0.406	0.719	0.660
Quality FE	YES	YES	YES	YES	YES	YES
County × Year FE	YES	YES	YES	YES	YES	YES
Tenant FE	NO	YES	YES	NO	YES	YES
Cluster by Tenant	YES	YES	YES	YES	YES	YES

Notes: The dependent variables are Winsorized Net Effective Rent and Net Effective Rent at the contract level. *Institutional Landlord (INST)* equals one if the property is owned by an institutional investor. Columns labeled *Basic* include only institutional ownership and fixed effects. *Full Controls* additionally include property characteristics and market controls. *Large Tenant* restricts the sample to properties leased by large tenants(large75). All specifications include quality fixed effects, county-by-year-month fixed effects, and tenant fixed effects. Standard errors (in parentheses) are clustered at the tenant level. Statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

Table 7
Institutional Ownership, Clustering, and Rents among Large Tenants

	Winsorized Rent		Net Effective Rent	
Sample:	Large75	Large70	Large75	Large70
INST × Cluster	-0.686**	-0.617**	-0.851**	-0.794**
	(0.297)	(0.279)	(0.341)	(0.327)
INST	-0.245	-0.282	-0.281	-0.300
	(0.233)	(0.221)	(0.273)	(0.265)
Cluster	0.516*	0.450	0.670**	0.622*
	(0.297)	(0.278)	(0.341)	(0.321)
ln(Age)	1.066***	1.041***	1.158***	1.115***
	(0.111)	(0.105)	(0.123)	(0.117)
ln(Size)	-1.655***	-1.622***	-1.822***	-1.791***
	(0.087)	(0.083)	(0.116)	(0.110)
ln(Dist. to Center)	0.330***	0.320***	0.435***	0.418***
	(0.119)	(0.113)	(0.138)	(0.131)
ln(#props in market)	-0.384***	-0.356***	-0.412***	-0.386***
	(0.082)	(0.077)	(0.093)	(0.088)
Lease Term	0.0381***	0.0374***	0.0424***	0.0417***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	22,114	24,362	22,114	24,362
Adjusted R^2	0.698	0.707	0.660	0.668
Quality FE	YES	YES	YES	YES
County × Time FE	YES	YES	YES	YES
Tenant FE	YES	YES	YES	YES
Cluster by Tenant	YES	YES	YES	YES

Notes: The dependent variables are *Winsorized Rent* and *Net Effective Rent* at the contract level. *Institutional Landlord (INST)* equals one if the property is owned by an institutional investor. *Cluster* indicates whether the property is located in a high-ownership cluster. (with number of active rented areas in the county ≥ 5. The interaction term *INST* × *Cluster* captures the differential effect of institutional ownership in clustered markets. The sample is restricted to properties leased by large tenants, defined using alternative thresholds based on tenant employment size (top 75% or top 70%). All specifications include property characteristics and market controls, quality fixed effects, county-by-time fixed effects, and tenant fixed effects. Standard errors (in parentheses) are clustered at the tenant level. Statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

Table 8
Summary of Mergers in the Analysis

Panel A: Summary of Mergers in the Analysis

Deal No.	Acquirer		Target		Announcement	Completion	# Prop
	Name	Type	Name	Type			
1	Blackstone	Eq. Fund	GLP	Inv. Mgr.	2019/6/2	2019/9/26	1117
2	GIC	SWF	Blackstone	Eq. Fund	2014/12/2	2015/2/27	1054
3	Walton Street Capital	Eq. Fund	DWS Group Americas	Inv. Mgr.	2007/4/23	2007/7/10	311

Panel B: Illustration of treated and control counties around mergers

County No.	County	# prop		# Prop gained	Group
		Acquirer	Target		
1	Tarrant County	38	12	12	Treat
3	Denton County	6	6	4	Treat
4	Collin County	3	2	2	Treat
6	Kaufman County	5	0	0	Control
8	Johnson County	0	3	0	Control

Panel C: Illustration of treated and control properties around mergers

Property No.	Name	Type	County	# of properties		Gained?	Group
				owned by acquirers	gained from merger		
1	Blackstone	Eq. Fund	Riverside County	22	6	NO	Treatment
2	Blackstone	Eq. Fund	Los Angeles County	190	69	NO	Treatment
3	Brookfield AM	Inv. Mgr.	Los Angeles County	0	0	NO	Control
4	Prologis	Pub. REIT	Los Angeles County	0	0	NO	Control
5	Blackstone	Eq. Fund	Los Angeles County	190	69	YES	Treatment
6	Blackstone	Eq. Fund	Sacramento County	85	0	NO	Control in Robustness Check

Panel A summarizes the three largest mergers in which the acquirers are institutional investors and don't overlap. Announcement and completion dates are obtained from SDC Platinum, and the number of properties involved is based on CoStar transaction data. Panel B illustrates how counties are classified into treatment and control groups. A treated county is defined as a county where the acquirer purchased one or more properties from the target firm. This classification allows us to treat the entry of institutional investors through mergers as a quasi-experimental setting for empirical analysis. Panel C further compares treated and control properties within treated counties. A treated property is defined as a property in a treated county that is owned by the acquirer. These properties are locally affected by the merger. Control refers to a property in a treated county that is owned by other investors excluding the target company. Properties located outside treated counties are excluded from Panel C.

Table 9
Difference-in-Differences Estimates of Rent Effects

	Dummy Treat		Continuous Treat	
Dep var:	Winsorized Rent	Net Effective Rent	Winsorized Rent	Net Effective Rent
Treat × Post	-4.169***	-4.251***	-1.313***	-1.294***
	(1.029)	(1.002)	(0.283)	(0.286)
Treat	2.272**	2.271**	0.706**	0.707**
	(0.999)	(0.985)	(0.300)	(0.301)
ln(Size)	-0.460	-0.547	-0.545	-0.458
	(0.400)	(0.439)	(0.438)	(0.399)
ln(Age)	-0.812	-0.810	-0.841	-0.842
	(0.926)	(0.975)	(0.975)	(0.926)
Lease Term	0.0155**	0.0178**	0.0178**	0.0154**
	(0.006)	(0.009)	(0.009)	(0.006)
ln(Dist. to Center)	0.256	-0.357	-0.333	0.273
	(1.500)	(1.560)	(1.564)	(1.503)
Observations	3,682	3,682	3,682	3,682
Adjusted R^2	0.895	0.884	0.884	0.895
Quality FE	YES	YES	YES	YES
Property FE	YES	YES	YES	YES
County × Time FE	YES	YES	YES	YES
Cluster by County	YES	YES	YES	YES

The dependent variable is net effective rent at the contract level. Columns (1) and (2) use a binary treatment indicator $I(\Delta\text{Properties} > 0)$ that equals one if the property is located in a treated county and is owned by the acquirer; columns (3) and (4) use a continuous treatment measure defined as $\ln(\Delta\text{Properties} + 1)$. The set of control variables includes rented area of the contract (ln(size)), property age (ln(age)), contract lease term, and distance to the market center. All specifications include quality fixed effects, property fixed effects, and county-by-time fixed effects. Standard errors (in parentheses) are clustered at the county level. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 10
Event Study of Rent Regression around Merger

	Dummy Treat		Continuous Treat	
Dep var:	Winsorized Rent	Net Effective Rent	Winsorized Rent	Net Effective Rent
Before × Treat	-1.337	-0.889	-0.286	-0.168
	(1.769)	(1.819)	(0.511)	(0.527)
After^1 × Treat	-4.098**	-4.234**	-1.262**	-1.283**
	(1.853)	(1.755)	(0.574)	(0.548)
After^2 × Treat	-5.118***	-4.955***	-1.570***	-1.532***
	(1.706)	(1.792)	(0.515)	(0.534)
After^3 × Treat	-2.783**	-2.719**	-0.782**	-0.764**
	(1.135)	(1.167)	(0.362)	(0.365)
Treat	2.454*	2.310	0.715*	0.677
	(1.360)	(1.412)	(0.418)	(0.427)
ln(Size)	-0.456	-0.543	-0.452	-0.539
	(0.400)	(0.440)	(0.399)	(0.438)
ln(Age)	-0.865	-0.853	-0.894	-0.886
	(0.936)	(0.983)	(0.932)	(0.980)
Lease Term	0.0155**	0.0178**	0.0154**	0.0178**
	(0.006)	(0.009)	(0.006)	(0.009)
ln(Dist to Market)	0.240	-0.354	0.248	-0.350
	(1.578)	(1.614)	(1.581)	(1.623)
Observations	3,682	3,682	3,682	3,682
Adjusted R^2	0.895	0.883	0.895	0.883
Quality FE	YES	YES	YES	YES
Property FE	YES	YES	YES	YES
County × Time FE	YES	YES	YES	YES
Cluster by County	YES	YES	YES	YES

The dependent variable is the net effective rent at the contract level. We use two treatment measures across the four columns: columns (1) and (2) use a binary treatment indicator $I(\Delta\text{Properties} > 0)$ that equals one if the property is located in a treated county and is owned by the acquirer; columns (3) and (4) use a continuous treatment measure defined as $\ln(\Delta\text{Properties} + 1)$. The key parameters of interest are event-time indicators defined relative to the merger completion date. *Before* corresponds to months -12 to -7; the omitted base period corresponds to months -6 to -1; $\textit{After}^1$ corresponds to months 1 to 6; $\textit{After}^2$ corresponds to months 7 to 12; and $\textit{After}^3$ corresponds to months 13 to 18. All specifications include quality fixed effects, property fixed effects, and county-by-time fixed effects. Standard errors (in parentheses) are clustered at the county level. Statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

Appendix

Appendix A. Variable Definition

Table A.1
Variable Definitions for Summary Statistics

Variable Name	Definition	Source
Panel A: CompStak Lease Contract-Level Variables		
Net effective rent	Monthly rent for newly signed contracts	CompStak
Winsorized rent	Net effective rent winsorized at 1%.	CompStak
age	Property age in years (current year minus construction year)	CoStar
Lease term	Length of new leasing contracts in months	CompStak
Transaction size	Square footage of rented space	CompStak
Quality	Property quality measure (Class A=1, B=2, C=3; 3=lowest)	CompStak
Multiple Landlord	Dummy variable equal to 1 if the tenant has an active rent in the same county from a different landlord	CompStak
Large Tenant(Large75)	Dummy variable equal to 1 for tenants above the 75th percentile of employment size	CompStak
Large Tenant(Large70)	Dummy variable equal to 1 for tenants above the 70th percentile of employment size	CompStak
INST	Dummy variable equal to 1 if the landload is an institutional investor. (if there are multiple owners, equal to 1 if one of the landloads is an institutional investor) Institutional investors include banks (BANK), investment managers (INVM), private equity funds (PEFU), pension funds (PENS), finance(FIN), insurance companies (INS), sovereign wealth funds (SWF), and open-end funds (OPENS).	CoStar
dist. to market	Distance to the market center in kilometers (MSA or County)	CoStar
#props in same MSA	Number of the landload's other active lease located within the same MSA	CompStak
#props in same county	Number of the landload's other active lease located within the same county	CompStak
Large Landlord(Size75)	Dummy variable equal to 1 for landlord above the 75th percentile of active rented space size	CompStak
Panel B: Trepp Property-Level Variables		

(continued) Variable Definitions for Summary Statistics

Variable Name	**Definition**	**Source**
EXP	Expenditure	Trepp
NOI	Net Operating Income	Trepp
DS	Debt Service	Trepp
Full Occ	Dummy variable equal to 1 for full tenant occupancy	Trepp
ln(app value)	Natural logarithm of most recent property valuation	Trepp
duration	Years since the most recent valuation	Trepp
#props in market	Number of properties owned by the same owner in the market (MSA or County)	CoStar
	Panel C: CoStar Transaction-Level Variables	
INST	Dummy variable equal to 1 if the buyer is an institutional investor	CoStar
Cluster	Binary indicator based on DBSCAN algorithm for geographic clustering	CoStar
age	Property age in years (current year minus construction year)	CoStar
RBA	Rentable Building Area in square feet	CoStar
dist. to market	Distance to the market center in kilometers (MSA or County)	CoStar
multi owner	Dummy variable equal to 1 if the purchase involves more than 1 buyer	CoStar
quality quartile	Property quality quartile (1=highest, 4=lowest) measured by transaction price quartile	CoStar

This table provides definitions for all variables included in the summary statistics (Table1). All financial variables in Panels B and E are winsorized at the 5% level. Financial variables in Panels B are scaled by current period revenue. In Panel C, DBSCAN algorithm is Density-based spatial clustering of applications with noise algorithm with the haversine metric. We use a data-driven approach to define the neighborhood radius. It is chosen as the median nearest-neighbor distance (from a 2% sample of properties). A cluster requires a firm to own at least three properties in a given year. We uses RBA (rentable building area) as weights.

Appendix B. Additional Results

This section presents additional results.

Table B.1
Regressions of Institutional Buyer on Cluster Indicator

Dependent variable:	INST			PEFU
	(1)	(2)	(3)	(4)
Cluster	0.030***	0.059***	0.059***	0.050***
	(0.006)	(0.006)	(0.006)	(0.005)
ln(age)		-0.033***	-0.025***	0.003
		(0.003)	(0.003)	(0.002)
ln(size)		0.076***	0.040***	0.021***
		(0.002)	(0.003)	(0.002)
ln(dist. to center)		-0.020***	-0.024***	-0.008**
		(0.004)	(0.004)	(0.003)
multi owner		0.151***	0.138***	0.053***
		(0.008)	(0.008)	(0.008)
Observations	173,700	167,390	134,413	111,462
Adjusted R^2	0.138	0.226	0.223	0.170
County×Year FE	YES	YES	YES	YES
Prop. quality quartiles	NO	NO	YES	YES
Cluster by County	YES	YES	YES	YES

The dependent variable is a dummy variable of owner's investor type. Columns (1)–(3) indicate whether the buyer is an institutional investor (INST). Column (4) indicates whether the buyer is a private equity fund (PEFU). The table reports regression estimates of institutional investment buyers on a cluster indicator using Costar transaction data from 2001–2022. The cluster indicator is constructed using the DBSCAN algorithm. All regressions include county-by-year fixed effects; columns (3)–(4) also control for property quality quartiles which is measured by transaction prices. Standard errors (in parentheses) are clustered at the county level. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table B.2

Regressions of Property Cash Flow on Investor Type

Dependent variable:	EXP	NOI	Debt	Full Occc
INST	-0.023***	0.022***	-0.016***	0.044***
	(0.008)	(0.008)	(0.006)	(0.017)
ln(age)	0.025***	-0.026***	-0.019***	-0.118***
	(0.006)	(0.005)	(0.005)	(0.012)
ln(size)	-0.018***	0.018***	-0.004	0.111***
	(0.004)	(0.004)	(0.003)	(0.013)
ln(dist. to center)	0.006	-0.006	-0.002	-0.0041
	(0.006)	(0.006)	(0.006)	(0.011)
ln(#props in market)	0.016***	-0.017***	-0.005**	-0.053***
	(0.002)	(0.002)	(0.002)	(0.007)
ln(value)	-0.008*	0.009**	0.003	-0.115***
	(0.004)	(0.004)	(0.004)	(0.014)
duration	-0.004***	0.005***	0.007***	0.005*
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	14,790	14,910	14,755	20,419
Adjusted R^2	0.263	0.271	0.335	0.184
County×Year FE	YES	YES	YES	YES
Cluster by County	YES	YES	YES	YES

The dependent variables are expenditure (EXP), net operating income (NOI), debt service (Debt), and an indicator for full tenant occupancy (Full Occ). The sample consists of cash flow statistics for properties that issued Commercial Mortgage-Backed Securities (CMBS) at any point between 2001 and 2022, based on data from Trepp. We match this CMBS data with our original dataset of industrial properties. The set of control variables includes property age (ln(age)), Rentable Building Area (RBA) of the property (ln(size)), distance to the market (MSA) center, and the number of properties owned by the same owner in the same year within the same market (MSA), most recent valuation (ln(value)), years since the most recent valuation (duration). Expenditure, net operating income, and debt are scaled by the revenue of the same year and are winsorized at the 5% level. Abnormal values, such as zeros, are excluded from the regression analysis. All regressions include county-by-year fixed effects. Standard errors (in parentheses) are clustered at the county level. Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.