The Columbia-CompStak Quality-Adjusted Commercial Real Estate Rent Index*

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Abstract

We construct a new quality-adjusted commercial real estate rent index for U.S. office, retail, and industrial markets using close to one million CompStak lease transactions from 2010-2025. A hierarchical hedonic framework with building-, block-, tract-, county-, MSA-, and state-level fixed effects allows us to control for both observable and unobservable quality, producing quality-adjusted rent indices. Nationally, these indices show that raw and simple hedonic rent series often overstate post-COVID recoveries, especially in office and retail, and at times understate pandemic-related declines, reflecting shifts in the quality mix of transacting properties rather than true market movements. Industrial rents, by contrast, exhibit only modest composition bias. Local indices further highlight stark geographic heterogeneity, including pronounced pandemic-related declines in San Francisco and only a modest post-pandemic recovery in Manhattan. Overall, our framework provides a more accurate measure of underlying commercial rent fundamentals by accounting for quality-driven composition effects that can distort inferences drawn from market averages.

JEL-Codes: R33, C43, C23

Keywords: Commercial Real Estate, Hedonic Rent Index, Composition Effects

*We thank CompStak for providing the data. The indices developed in this paper will be made publicly available for research purposes. Corresponding author: Stijn Van Nieuwerburgh svnieuwe@gsb.columbia.edu, 665 West 130 Street, New York, NY 10027, USA.

1 Introduction

This paper constructs a quality-adjusted commercial real estate rent index. Our index provides high-frequency measures of rent inflation for different commercial real estate sectors and across a broad range of geographical markets in the U.S. Using our rent index, we shed new light on the evolution of commercial real estate in the past 15 years. We find that, on a quality adjusted basis, the recovery of office rents during the post pandemic era was substantially weaker than what is suggested by the raw data. Similarly, our index suggests that rent growth in the retail and industrial sectors has been weaker in recent years relative to what would be inferred based on simple averages. The divergence between our quality-adjusted index and the raw data reflects compositional variation and underscores the value of our index in assessing the true strength of underlying rental market conditions.

Our main data source is commercial real estate lease data compiled by CompStak between 2010 and 2025. CompStak compiles a national database of commercial real estate leases by crowd-sourcing information from a network of verified brokers, appraisers, and researchers. The accuracy of every rental lease is verified by expert analysts and machine learning algorithms. For each lease, the data records, for example, the square footage being leased, the starting rent and rent schedule over the lease term, concessions including tenant improvements and free rent, the type of space being leased (e.g., office, industrial, retail), the lease type, the building address and its physical characteristics, and the dates on which the lease is signed and when it commences. Our main measure of rent is net effective rent per square foot. We also construct indices for starting rents, tenant improvements, and free rents. To assess the coverage of CompStak, we compare the occupied office inventory in our data to the occupied office inventory reported by Cushman & Wakefield. In major markets like Manhattan and San Francisco, CompStak covers around 90% of the office market, while in smaller markets the coverage is lower.

To construct a quality-adjusted rent, we estimate a hedonic regression with hierarchical geographical fixed effects. This allows us to control for both observed and unobserved lease characteristics. Controlling for the quality of the leased space is key since simple averages of rents in each time period do not account for the changing composition of the transacted units and will therefore likely be biased. While CompStak records rich lease and building hedonics that allow us to control for a host of observed characteristics, a main challenge is that some quality characteristics may still be unobserved. To address this challenge, we employ a hierarchical geographical fixed effects approach. Namely, we control for unobserved (and time-invariant) characteristics at the building level with building fixed effects, at the block group level with Census block group fixed effects, and so on and so forth till state level characteristics with the state fixed effects. The hierarchical structure allows us to control for unobservable characteristics at the most granular level possible for each lease. For the vast majority of office buildings, the data includes a large enough number of leases that enables us to reliably estimate building level fixed effects. For most retail and industrial buildings, we do not always have enough leases to estimate building level fixed effects. For such leases, we control for unobservable characteristics with Census block group fixed effects (if the data includes enough leases within the block group) or less granular fixed effects like census tract, county, MSA, or state, in decreasing order of data availability.

We construct rent indices for office, retail, and industrial real estate. For each sector, we provide a national index at the monthly frequency as well as indices for a large number of cities and Metropolitan Statistical Areas (MSAs) at a quarterly frequency. Our index covers 170 geographical office markets in the U.S., 89 retail markets, and 51 Industrial markets. A key advantage of our index relative to alternative commercial real estate rent indices—e.g., the CBRE Econometric Advisors Asking Rent Index or the index developed by An et al. (2016)—is its broad geographical and sectoral coverage. We refer to our constant-quality rent index as the CQR index henceforth.

We use our new CQR index to document new facts on the dynamics of commercial real estate markets in the U.S. A main result is that the recovery of office rents since the onset of COVID-19 has been substantially weaker than what one might conclude based on simple data averages. Namely, the compound annual growth rate (CAGR) of office rents between December 2019 and August 2025 was only 0.54% according to our index, compared to 2.74% according to the raw data. This suggests that much of the apparent recovery in raw office rents reflects composition effects, particularly the concentration of lease executions in higher-quality buildings and/or higher-rent markets during this period. This interpretation is consistent with Gupta, Mittal and Van Nieuwerburgh (2025), who show that post-pandemic office values have not recovered in aggregate and that resilience is concentrated in higher-quality buildings and prime locations. Similar patterns, albeit less stark, emerge in the retail and industrial sectors.

To illustrate the importance of our hierarchical geographical fixed effects approach, we also construct a simple hedonic index that controls for observables and MSA fixed effects but not for more granular fixed effects from building/block group/tract/county. Post-pandemic office rent growth according to this traditional hedonic index is weaker than implied by the raw data but stronger than implied by our CQR. This divergence underscores the importance of controlling for unobservable quality characteristics. As further evidence for the strength of our approach, we show that augmenting the simple hedonic model with hierarchical geographical fixed effects substantially strengthens the model's explanatory power. The R^2 of the simple hedonic model is 0.61 for office rents, 0.58 for retail rents, and 0.71 for industrial rents, while the R^2 of our hierarchical geographical fixed effects model is 0.85 for office, 0.81 for retail, and 0.82 for industrial.

Commercial real estate dynamics are inherently local. By constructing rent indices for a large number of cities and MSAs, we are able to analyze the heterogeneous recovery patterns from the COVID-19 pandemic across geographical markets. Office markets across the country exhibit similarly steady rent growth before 2019, but markedly different trajectories thereafter. For example, Manhattan's quality-adjusted net effective rent shows a sharp decline in the pandemic-era, with rent barely recovering to its pre-pandemic level by mid-2025, Dallas's growth rate remains relatively stable throughout the pandemic, while San Francisco stands out for its prolonged decline during and after the pandemic. Industrial markets across the country show a pronounced rent acceleration beginning in 2020, reaching a peak in 2022, followed by varying degrees of correction. The pullback is particularly noticeable in Los Angeles. Retail rents in Manhattan exhibit a moderate recovery from the pandemic dip; they remain lower than pre-pandemic levels in San Francisco.

Our main analysis considers net effective rents. We decompose the latter and estimate separate constant-quality indices for starting (taking) rents, tenant improvements, and free rent. Our analysis shows that tenant concessions have expanded markedly over the decade before COVID-19. For example, in Manhattan's office market, tenant-improvements drift from 6% to 12% of lease value and free rent increases from 4% to 8.5% between 2010 and 2019. Concessions have remained at historically elevated levels during the post-pandemic era. Failing to adjust for latent quality results in concession estimates that are too low.

Finally, we study comovement of local CQR indices across markets, finding increasing regional integration in industrial rents. Office markets, in contrast, show fragmentation with local market dynamics rising in importance after the pandemic. We study correlation with local macro-economic variables and with residential rent indices. Finally, we consider richer functional forms for how the building and lease features affect rents using two different machine learning techniques. We verify that our CQR indices are largely unchanged.

2 Related Literature

This paper combines aspects of the two prevailing approaches for constructing rent indices, namely the repeat-rent approach and the hedonic approach. We briefly discuss these two approaches. Most applications are to residential real estate, but there is work on commercial real estate as well.

Repeat-rent indices are constructed by comparing rents for the same unit across time. The underlying framework originates from the repeat-sales literature, which formalized within-asset differencing and time-dummy estimation as a constant-quality identification strategy (Bailey, Muth and Nourse, 1963; Case and Shiller, 1989; Goetzmann, 1992; Fisher, Geltner and Webb, 1994). Subsequent extensions generalize this framework to granular and thin markets through hierarchical modeling, real-time revision schemes, and mixed-frequency estimation (Francke and van de Minne, 2017; van de Minne et al., 2020; Francke and van de Minne, 2022). The key advantage of the repeat-rent approach is that it allows controlling for unobservable (time-invariant) characteristics. The main drawback is that it requires observing the same units being sold or rented repeatedly, which usually results in the loss of most transaction observations.

Hedonic approaches identify constant-quality price movements by explicitly modeling how observable property attributes contribute to observed price or rent levels. To the extent that renovation is included among these attributes, the model can capture quality improvements over time, helping address a key limitation that often affects repeat-rent indices. The underlying theory of the hedonic framework views goods as bundles of characteristics, each carrying an implicit price that equilibrates supply and demand in differentiated markets (Court, 1939; Rosen, 1974). Building on this foundation, the approach has been formalized for real estate (Wheaton and Torto, 1994; de Haan and Diewert, 2013; Silver, 2016).The key advantage of the hedonic approach is that it does not require observing the same units being leased repeatedly. The drawback is that it does not control for unobservable characteristics which can bias the estimation.

Several papers bridge the gap between repeat-sales and hedonic models by adopting hybrid specifications. Case and Quigley (1991) propose splitting the sample into (i) single-sale observations, which are modeled with a standard hedonic regression, and (ii) repeat-sale observations, which are modeled in first differences (or with property fixed effects) so that time-invariant unobservables are differenced out; the two subsamples are then stacked and the index is estimated on both subsamples jointly. The challenge with this approach is that it treats the two subsamples as governed by different estimating equations, which creates a discontinuity at the boundary between single- and repeat-sale properties. Francke and van de Minne (2020) provide a random-effects hedonic framework that unifies these pieces, and combine it with machine-learning methods in Francke and van de Minne (2024).

A fundamental challenge in commercial real estate rents is that repeated leases on the exact same space are rare. This is not only because leases are long-term, but mostly because rental space within office, retail, and industrial buildings can typically be subdivided arbitrarily. While one can observe repeated transactions on the same (residential or commercial) property or repeated rents on the same residential rental unit, in commercial real estate this is typically not the case. The aforementioned methods for bridging the gap between repeat-rent models and hedonic models are therefore challenging to implement in the context of commercial real estate rents. To overcome this challenge, we propose a hierarchical fixed effect approach that allows us to control for unobservable lease characteristics without requiring that we observe the exact same rental space being leased repeatedly.

Having outlined the methodological foundations, we next turn to their empirical implementations across settings: first in residential markets, where both approaches originated and remain most developed, and then in commercial markets, where data constraints have historically limited their application but recent advances are closing this gap.

In residential settings, both strands have been extensively implemented and refined. The repeat-rent framework applies the repeat-sales methodology to rental markets (Ambrose, Coulson and Yoshida, 2015, 2023; Adams et al., 2024; Abramson, De Llanos and Han, 2025). The same principle has also been adopted in industry practice, underpinning indices such as Zillow's Observed Rent Index (ZORI) and CoreLogic's Single-Family Rent Index (SFRI). Hedonic methods, long used in residential price measurement (Francke and De Vos, 2000; Sirmans et al., 2006; Diewert, de Haan and Hendriks, 2015; Reusens, Vastmans and Damen, 2023), have likewise been applied to rents (Hill and Syed, 2016; Wu, Deng and Gyourko, 2012; Löchl and Axhausen, 2010; Pholo Bala, Peeters and Thomas, 2014; McCord et al., 2014).

In commercial settings, index construction was long constrained by limited data. Wheaton and Torto (1994) construct a hedonic office rent index at the national level and for five major markets. An et al. (2016) focus on properties owned by the National Council of Real Estate Investment Fiduciaries (NCREIF) and construct commercial rent indices at the national level and for a limited number of geographical markets. The key advantage of our index is its broad geographical coverage. Most closely related to our index is the CBRE Econometric Advisors Asking and Taking Rent Index, which is the successor of the Torto-Wheaton Research (TWR) Index (Wheaton, Torto and Southard, 1997). The CBRE indices offer limited coverage and are not publicly available. In contrast, our index provides broader geographical coverage and will become publicly available. CompStak constructs a quarterly hedonic index from starting rents using observable characteristics, without controlling for unobserved building heterogeneity. Our main index is based on net effective rents and controls for unobservables, which we show substantially improves its explanatory power.

This paper contributes to the literature in two ways. First, we estimate a hedonic rent index that controls for rich characteristics, and we allow hedonic coefficients to differ across markets and over time. Second, while our approach is not a repeat-rent design, we absorb persistent unobserved quality with building fixed effects—and, where panels are thin, with a hierarchical fallback to block group or tract/county/MSA/state fixed effects—thereby retaining substantially more observations than methods that require repeat observations on the identical unit, expanding coverage without sacrificing identification from within-location variation. Jointly, the design blends the strengths of hedonic modeling (explicit, flexible quality adjustment) with repeat-rent style identification (netting out time-invariant quality via building fixed effects), yielding a constant-quality index with broad coverage and cross-market comparability. This structure allows us to recover market rent dynamics net of shifts in leasing composition. In particular, it helps mitigate selection bias when, for example, only higher-quality assets transact during downturns, causing raw indices to overstate market strength.

3 Data

We construct our commercial rent indices using proprietary datasets from CompStak, which collects and standardizes information on commercial lease transactions across major U.S. markets. CompStak gathers lease-level data from a network of commercial real estate professionals, including verified brokers, appraisers, and researchers, who contribute transaction details to the platform. Submitted records are compiled into a standardized dataset containing information on lease terms, rents, property characteristics, and tenant types. Because the raw data nonetheless contain inconsistencies in geography, timing, and lease attributes, we implement a structured cleaning process to ensure that our analytical sample is accurate and comparable across markets.

Table A.1 documents the sequence of cleaning steps from raw data to the final cleaned dataset. Leases with invalid or ambiguous locations are removed, and each remaining record is mapped to a unique geography based on its geolocation. We then standardize temporal and space-type variables, drop leases missing essential information, and exclude subleases. Next, we construct regression covariates and assign hierarchical geographical fixed-effect identifiers, applying minimum-observation thresholds at each level to ensure stable estimation, as discussed further below. Finally, we remove leases with invalid lease terms and invalid or missing log NER values, yielding a cleaned, regression-ready dataset.

The cleaned dataset contains 1,128,063 leases across the Office, Retail, and Industrial sectors. Temporally, the dataset spans from 1965 to 2025, with substantial growth in coverage after 2000 reflecting both the expansion of the CompStak platform and the digitization of commercial real estate data. Our estimation window focuses on the period after 2010, which contains 74.1% (895, 461) of the original observations and offers consistent, high-quality coverage across markets.

Our estimation sample is composed of 55% Office leases, 20% Retail leases, and 25% Industrial leases (see Table A.2). CompStak's raw space-type classifications also include a "Flex/R&D" category, which we recode into the Industrial sector (a subtype category is created to preserve the Flex/R&D classification). The index for industrial space is estimated at the MSA level whereas for office and retail space, it is estimated at both the MSA and city level.

The dataset exhibits broad geographic coverage across the United States. The largest concentrations of leases are in major states such as California, Texas, and New York. The data span 914 MSAs nationwide, where MSAs are defined according to 2025 Core Based Statistical Areas (CBSA) shapefiles from the Census (last updated in September 2025). Major metropolitan areas—including San Francisco–Oakland–Fremont, Dallas–Fort Worth–Arlington, Los Angeles–Long Beach–Anaheim, New York–Newark–Jersey City, and Houston—account for large shares of observations. Table A.3 reports the share of observations in the 15 largest markets. Although coverage is concentrated in primary and large secondary markets, this distribution aligns with where most commercial leasing activity occurs and provides the data density necessary for reliable market-level estimation.

The final estimation sample includes 51 industrial MSAs, 58 office MSAs, and 55 retail MSAs. In addition, for markets that meet the city-level data requirements, we estimate a parallel set of city-level indices, yielding 118 office cities and 39 retail cities. Coverage varies substantially across markets, with major office markets such as Manhattan, San Francisco, Los Angeles, Chicago, and Washington, DC containing the largest numbers of observations. Table A.4 shows the top-10 markets in each space type by number of lease observations.

We next document the structure of the final estimation sample and the availability of key variables. Our primary outcome variable is the log of net effective rent (NER), which incorporates base rent, free rent, tenant improvement allowances, and lease term. Table A.5 shows data coverage statistics. Continuous controls include log lease size (100% coverage), log building size (78.5% coverage), log lease term (99.8% coverage), log renovation-adjusted age (96% coverage), and log average floor occupied (38.5% coverage). When the renovation date is not available, renovation-adjusted age is equal to building age (years between the transaction data and construction date). Categorical variables include lease type (83.3% coverage), transaction type (74.8% coverage), tenant industry (67.1% coverage), building class (85.6% coverage), space subtype (20% coverage), and a Central Business District (CBD) dummy (100% coverage). The lease types are: NNN, full service, modified gross, net, net of electric, and gross. The transaction types are: new lease, renewal, expansion, and extension. The building classes are A (highest quality), B, and C, as defined by Compstak. The most important space subtypes in each space type are listed in Table A.6. The CBD dummy is obtained from Koijen, Shah and Van Nieuwerburgh (2025). Hierarchical geographical fixed effects have complete coverage, as does transaction square footage, which we use as a regression weight. We do not drop observations if one or more covariates are missing. Rather, we include a dummy variable for whether a given covariate is missing in the regression. The coefficient on the missing characteristic can be informative about non-random absence of covariates and the impact on rents.

The dataset also displays substantial heterogeneity in the distribution of property class (Table A.7) and the distribution of lease size (Table A.8). Lease size is heavily right-skewed. The largest Industrial leases tend to be much larger than in Office or Retail. The highest proportion of class-A properties are in the office sector, with distributions between class- A, B, and C more even for Retail and Industrial.

Representativeness To assess CompStak's data coverage for Office markets, we compare the square footage of outstanding leases in CompStak to the occupied inventory reported by Cushman & Wakefield. We identify outstanding leases as those that are active as of September 30, 2025, i.e., leases where the commencement date is on or before this date and the expiration date is on or after this date. We then calculate coverage as the ratio of CompStak's outstanding lease square footage to occupied office inventory, where occupied inventory is defined as total office inventory multiplied by (1 - direct vacancy rate), with direct vacancy rates excluding subleases as reported by Cushman & Wakefield. Table A.9 shows CompStak's data coverage for 26 city-level office markets in our analysis. Washington, DC shows the highest coverage at 101.94%, indicating that CompStak captures nearly all occupied office space in this market. Manhattan and San Francisco also show very high coverage rates of 86.54% and 94.32% respectively, reflecting CompStak's strong presence in these major office markets. Several markets show good coverage rates, including Seattle (67.47%), Tampa (63.93%), Chicago (56.45%), Austin (52.91%), and Charlotte (51.78%). Markets with lower coverage rates include San Jose (6.23%), Oakland (9.37%), and Las Vegas (15.31%), which may reflect differences in CompStak's user adoption, data collection intensity, market definitions, or market characteristics across these metropolitan areas. The variation in coverage across markets suggests that while CompStak provides comprehensive coverage in many major office markets, coverage is more limited in some secondary markets, which is important to consider when interpreting our results.

Data Updates To assess how CompStak's data collection evolves over time, we compare the October 2025 and December 2025 datasets. CompStak added 12,799 leases over this two-month period (roughly 1.5% of the dataset). Manhattan Office added 310, increasing its share of total leases by 1.2% points. Table A.10 illustrates that newly-reported leases differ systematically from existing leases in terms of lease size (for Manhattan), net effective rent level (Manhattan and national), and proportion of class-A (Manhattan). Simply put, newly-reported leases tend to be larger, more expensive, and more likely to be in class-A properties. This non-random nature of initial reporting gets corrected in subsequent data collections, but highlights the importance of proper quality adjustment.

4 Rent Index

To construct a quality-adjusted commercial rent index, we first estimate the following weighted least squares (WLS) hedonic regression using Compstak commercial real estate lease-level transaction data on the full **national** sample:

$$\log R_{ijst} = \alpha_{st} + HGFE_j + \beta X_{ijst} + \epsilon_{ijst} \tag{1}$$

where R_{ijt} is the net effective rent per square foot in nominal dollars for lease i in building j of space type $s \in \{\text{Office, Retail, Industrial}\}$ executed at time t. The variable $HGFE_j$ is our hierarchical geographic fixed effect, discussed below, which helps control for unobservable quality differences across leases. X_{ijst} is a vector of lease and building characteristics which help control for observable quality differences across leases. Each lease is weighted by its transaction square footage. Estimating a weighted least squares regression ensures that every square foot–rather than every lease–is weighted equally, so that larger leases are given more weight in our index. We estimate this specification separately for each space type s. Our main coefficients of interest are the space type-specific time fixed effects $\{\alpha_{st}\}_{t=1}^{T}$, which represent the average rent level over time net of controls.

To convert these estimates into an index that tracks rent changes over time in nominal dollars per square foot, we compute the transformation:

$$R_{st} = e^{\log \bar{R}_{st_0} + \alpha_{st} - \alpha_{st_0}} \tag{2}$$

where t_0 is the base period to which we normalize our index (2019Q4) in our model and R_{st} is our estimate of the constant-quality rent (henceforth, CQR) index at time t for space type s. We normalize the rent index in the base period equal to the average of the raw rent series for that space type in the base period t_0, $\bar{R}_{st_0}$. The alternative is to pick a specific type of lease as the benchmark, evaluating the model at a specific covariate vector.[1]

Analogous to equation (1), we estimate separate constant-quality rent indices for each local market m and space type s:

$$\log R_{ijmst} = \alpha_{mst} + HGFE_j + \beta X_{ijmst} + \epsilon_{ijmst} \tag{3}$$

Similar to equation (2), the CQR index for each market m with space type s is computed as

$$R_{mst} = e^{\log \bar{R}_{mst_0} + \alpha_{mst} - \alpha_{mst_0}} \tag{4}$$

The only substantive difference between the national and market-specific indices is that the national estimation can be done at the monthly level rather than the market's quarterly level since there are enough leases each month at that level of aggregation. This provides for a more timely but geographically coarser index of the evolution of rents in office, retail and industrial markets. Throughout our estimation exercise, our covariates and the dependent variable are winsorized at the 1^{st} and 99^{th} percentiles to prevent outlier leases from unduly affecting our estimation results.

[1] For example, we could normalize the index to the net effective rent in a base period on a new, 25,000 square feet gross lease on the second floor of a 200,000 square foot class-A office building. Our normalization improves interpretability, but depends on the specific composition of leases signed in the base period.

Hierarchical Geographic Fixed Effects A central contribution of our methodology is the construction of hierarchical geographic fixed effects, the term $HGFE_j$ in the equations above. Given that the Compstak data provides a geocode (latitude and longitude) of the building to which the lease pertains, we are able to map each lease to increasingly aggregate geographical areas: Census block groups, tract, county, and Metropolitan Statistical Areas (MSA). In the HGFE framework, each lease is assigned to the most granular geography with at least five observations: building FE when there are at least five leases present in the sample for that building, block group FE if there are not five leases in the building but there are at least five leases in the Census block, ZIP code FE otherwise, then City FE, MSA FE, and State FE if all else fails. This structure maximizes the granularity of geographic controls while maintaining statistical stability.

Table 1 describes the number of lease observations that are assigned to each kind of HGFE. The first three columns are for the three space types, the fourth column for the overall sample. The last column reports the distribution of HGFE for the overall sample. We are able to include a building FE for over half of all lease observations and either a building or a block group FE for almost 90% of lease observations. Fewer than 10% of leases get assigned a county, MSA or state FE. For office leases, we have the highest share of building FE. Given that industrial buildings are more likely to be single-tenant and that industrial leases tend to have longer maturities, the industrial sector has a lower fraction of building FEs.

Table 1: HGFE Distribution

Level	Office	Retail	Industrial	Total	Percentage
Building	382969	41094	77387	501450	56.0%
Block group	82311	83891	126014	292216	32.6%
Tract	7800	14597	4200	26597	3.0%
County	19233	41599	13162	73994	8.3%
MSA	35	228	43	306	0.0%
State	165	625	108	898	0.1%

5 Results

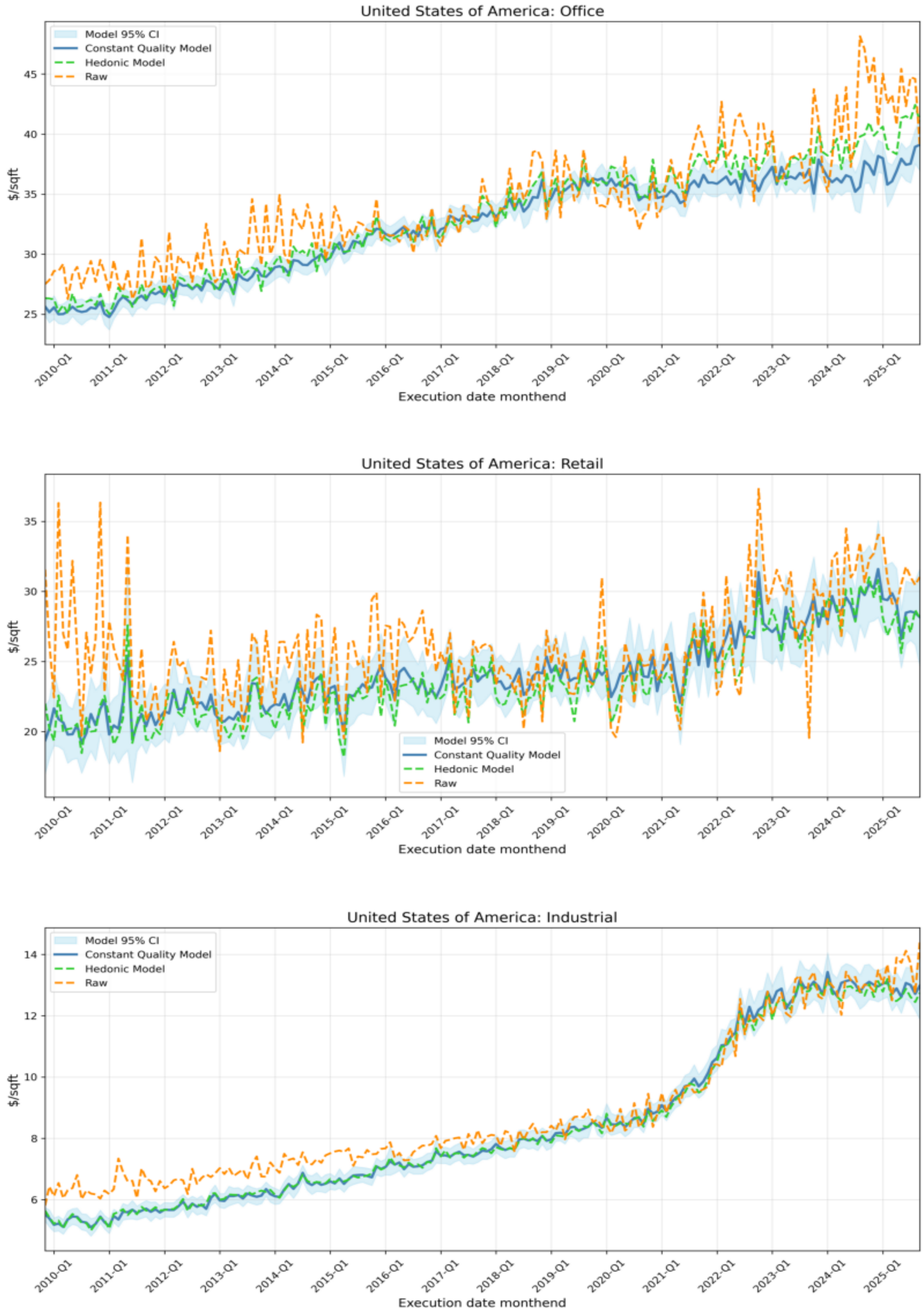
This section presents and interprets the estimated quality-adjusted commercial real estate rent indices across major U.S. metropolitan markets and sectors. We first examine the evolution of office, retail, and industrial rents nationally and in key cities, highlighting differences between our CQR index, standard hedonic indices, and the raw data. We then analyze alternative commercial real estate metrics, such as tenant improvements and free-rent concessions, using Manhattan offices as a case study. Finally, we study cross-market differences in hedonic parameter shifts during the COVID-19 period and identify where quality adjustment matters most. Throughout, we emphasize how controlling for lease, building, and location characteristics reshapes the interpretation of commercial rent trends. Taken together, the results underscore the value of the proposed methodology in isolating underlying market-driven rent dynamics from both contractual variation and compositional shifts in quality.

National CQR Indices We begin by analyzing national trends in commercial real estate rents. Figure 1 presents national-level indices across office, retail, and industrial spaces. While the period since 2010 shows a general upward trend in nominal net effective rents, there are notable differences between our rent index (solid blue line) and the raw data (dashed orange line). Our constant-quality rent (CQR) index displays considerably less volatility than the raw series between 2010 and 2019, prior to the pandemic. It also shows a much smaller decline at the onset of the COVID-19 pandemic in the first half of 2020. Most notably, the CQR index indicates a much smaller growth in the post-COVID years in rents, again with much lower volatility. The raw data also shows large increases in rents across all three sectors in the final quarters of the sample, gains that are largely absent in our CQR index. In the case of office space, our CQR series indicates only modest cumulative nominal rent growth, measured by a compound annual growth rate (CAGR) of 0.54% between December 2019 and August 2025, compared with 2.74% in the raw data. The smooth trajectory of the CQR index suggests that much of the apparent recovery in raw office rents reflects composition effects, particularly the concentration of lease executions in higher-quality buildings and/or higher-rent markets during this period of stress for commercial real estate (CRE) markets.

The dashed green line is a traditional hedonic rent model that controls for observable lease characteristics in the vector X as well as MSA fixed effects, but not for hierarchical geographic fixed effects at the building, block group, tract, or county levels. The office market generally displays dynamics similar to our constant-quality index, which controls for finer geography. However, during the pandemic recovery period (from 2023 onward), it indicates a higher level of rents than our richer CQR index. This divergence underscores the importance of controlling for unobservable quality characteristics when assessing the true strength of underlying market conditions.

The retail sector presents a more volatile picture in the raw series, with net effective rents oscillating over time. Premium leases in high-street locations and other compositional factors can distort raw aggregates, while the wide dispersion of rents across retail property types and locations underscores the inherent heterogeneity of the sector. In contrast, our quality-adjusted index remains considerably more stable. Overall growth has been modest over the past 15 years, as retail has been hit hard by the steady rise of e-commerce throughout this period. The divergence between our index and the raw series is also evident during the final quarters of our sample, with our quality-adjusted index indicating a lower underlying level of market rents–and, consequently, a weaker post-pandemic retail recovery–than suggested by the raw data.

Figure 1: National Net Effective Rents



In the industrial sector, all three indices track each closely, underscoring modest composition effects, possibly due to the relative homogeneity of industrial real estate. All three show pronounced acceleration in rents beginning in 2020, as the e-commerce boom accelerated during Covid-19 pandemic. They all peak around 2022.Q3, when higher interest rates and a construction boom slowed down the industrial market. This shows that the industrial boom was broad and wide, both across geographies and quality segments. In such a scenario, composition bias is minimal. The end of the sample shows divergence between raw (and hedonic) series and our CQR index. With new supply coming online in several markets, leasing activity appears increasingly concentrated in the highest-quality assets and top-performing locations. This compositional bias can inflate the apparent strength of the market in the raw data, obscuring recent signs of softening conditions in the broader industrial sector that our CQR index more accurately reflects.

An important observation is that our quality adjustment also corrects for end-of-sample bias, which arises because the most recent periods tend to be populated disproportionately by high-profile leases. These are often large, institutionally-brokered transactions in prime locations that enter the dataset earlier than smaller or secondary-market deals, artificially inflating late-sample rent estimates in the raw data and hedonic indices. By anchoring prices to a consistent set of properties and estimated quality attributes, our CQR model mitigates this imbalance, ensuring that the apparent late-sample surge reflects true market dynamics rather than temporary reporting distortions.

To better understand the mechanisms underlying the CQR index, it is instructive to examine the hedonic regression coefficients and overall model fit. Table 2 reports our CQR model in the first column and the standard hedonic model in the second column of each panel. Across sectors, the coefficient patterns are economically intuitive but show that the CQR specification typically dampens sensitivities relative to the hedonic model–consistent with its ability to filter out composition effects and unobserved heterogeneity. For all three property types, lease term has a positive and significant relationship with rent levels, reflecting the term premium associated with longer contractual commitments.[2] Building renovation-adjusted age carries a negative sign across all sectors, indicating that newer or recently renovated buildings command rent premiums. The higher the floor the leased space is on, the higher the rent. Finally, the CQR models consistently exhibit higher explanatory power than the hedonic model, with R^2 values of 0.85 for office, 0.81 for retail, and 0.82 for industrial, compared to 0.61, 0.58, and 0.71, respectively. This demonstrates that incorporating hierarchical geographic fixed effects at granular levels significantly improves model fit and provides a more reliable measure of underlying rent dynamics.

[2] Since we work with nominal leases, landlords seek protection against inflation by negotiating rent step-ups in later phases of the lease. The longer the lease, the more rent growth is usually contractually agreed upon. These rent bumps increase the net effective rent, also because the NER computation ignores the time value of money.

Table 2: National Results (CQR vs Hedonic)

	Office		Retail		Industrial	
	CQR	Hedonic	CQR	Hedonic	CQR	Hedonic
Log Lease Size	-0.002**	-0.001	-0.234***	-0.246***	-0.073***	-0.091***
	(0.001)	(0.001)	(0.004)	(0.005)	(0.002)	(0.002)
Log Building Size	0.006	0.008***	-0.019***	0.006	-0.023***	-0.036***
	(0.004)	(0.002)	(0.003)	(0.005)	(0.003)	(0.003)
Log Lease Term	0.040***	0.076***	0.181***	0.202***	0.075***	0.097***
	(0.002)	(0.003)	(0.005)	(0.007)	(0.002)	(0.003)
Log Renovation Age	-0.024***	-0.041***	-0.049***	-0.046***	-0.030***	-0.030***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
Log Average Floor	0.031***	0.072***	-0.072	0.580	0.573***	1.331***
	(0.002)	(0.003)	(0.066)	(0.383)	(0.097)	(0.116)
Clear Height Std	-	-	-	-	0.004	-0.001
					(0.003)	(0.003)
1_{CBD}	0.206**	0.254***	-0.032	0.601***	0.106*	0.294***
	(0.063)	(0.005)	(0.109)	(0.025)	(0.042)	(0.016)
1_{missing}(Log Building Size)	0.052	0.071**	-0.242***	-0.011	-0.298***	-0.474***
	(0.046)	(0.026)	(0.031)	(0.050)	(0.035)	(0.029)
1_{missing}(Log Lease Term)	0.126***	0.169***	0.453***	0.516***	0.218***	0.239***
	(0.029)	(0.051)	(0.041)	(0.061)	(0.046)	(0.046)
1_{missing}(Log Renovation Age)	0.020	0.019	-0.105***	-0.138***	-0.019*	-0.017
	(0.012)	(0.014)	(0.014)	(0.018)	(0.010)	(0.011)
1_{missing}(Log Average Floor)	0.056***	0.088***	-0.063	0.325	0.405***	0.931***
	(0.004)	(0.006)	(0.047)	(0.269)	(0.067)	(0.080)
1_{missing}(Clear Height Std)	-	-	-	-	0.027***	0.060***
					(0.005)	(0.005)
Lease Type	✓	✓	✓	✓	✓	✓
Transaction Type	✓	✓	✓	✓	✓	✓
Tenant Industry	✓	✓	✓	✓	✓	✓
Building Class	✓	✓	✓	✓	✓	✓
Space Subtype	✓	✓	✓	✓	✓	✓
Hierarchical FE	✓	-	✓	-	✓	-
MSA FE	-	✓	-	✓	-	✓
Observations	489264	489264	181444	181444	219689	219689
R^2	0.848	0.612	0.806	0.584	0.820	0.714

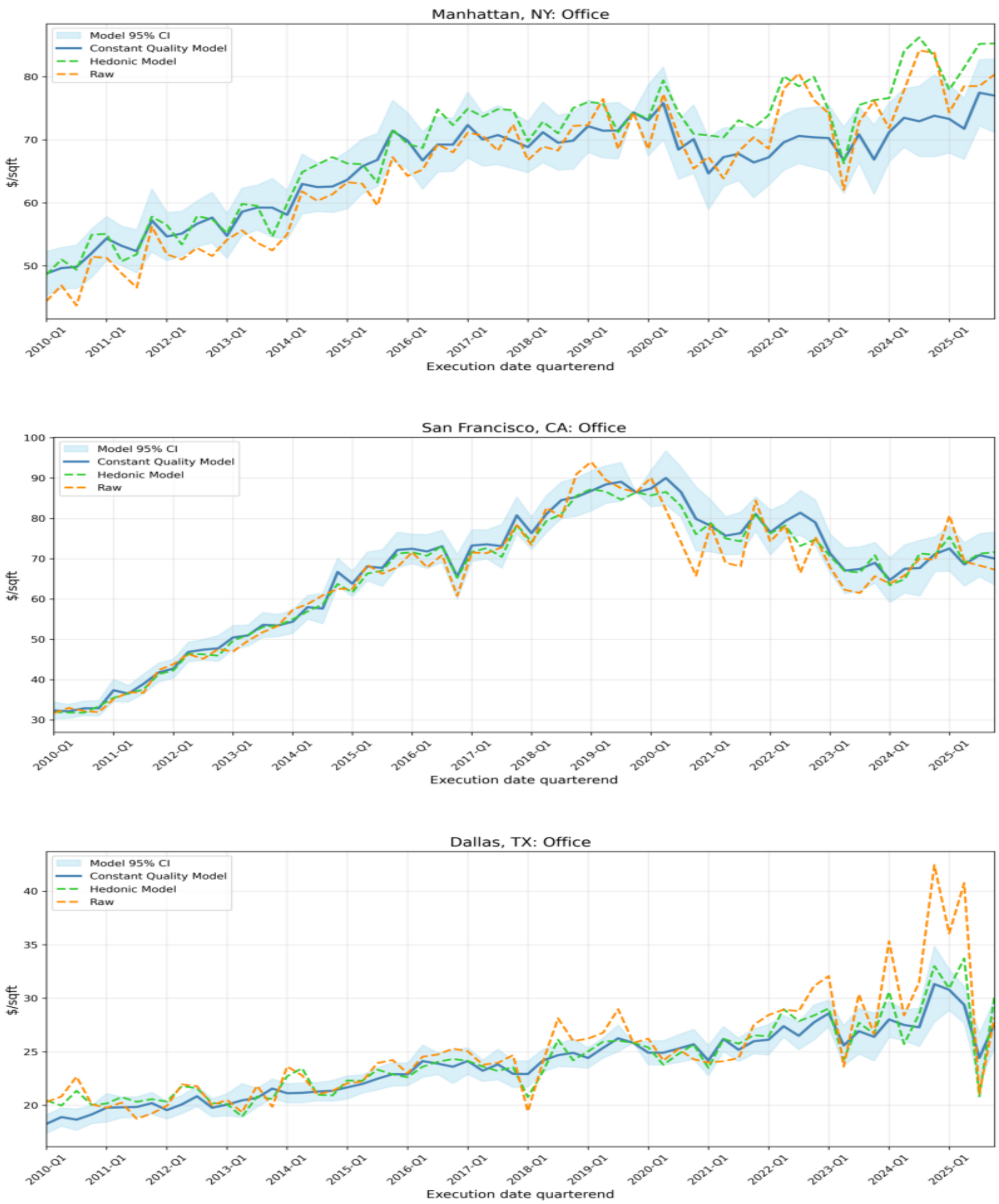
Market CQR Indices We next turn to local markets. Commercial real estate dynamics are inherently local, so the market-sector-level specification is central to our analysis. Estimating indices at this finer level provides a clearer view of local demand and supply conditions, captures regional heterogeneity in recovery patterns from the pandemic, and enhances the precision of our constant-quality rent estimates by allowing the coefficients on the quality adjustments to vary across markets. Constructing local indices not only enables us to measure quality-adjusted rent changes within each market, but also allows us to disentangle how much of the composition effects observed in the national series arise from shifts across markets versus changes within them. We produce the market CQR indices at quarterly frequency.

Figures 2–4 compare the evolution of net effective rents under our CQR model, the standard hedonic model, and the raw series for three illustrative major markets in each space type. Across all panels, the CQR model yields a smoother trajectory, attenuating volatility by controlling for changes in lease composition. This feature is most pronounced in markets such as Dallas office and San Francisco retail, where the raw series exhibits large quarter-to-quarter swings not reflected in fundamentals.

Figure 2 shows that Manhattan, San Francisco, and Dallas office markets exhibit steady nominal growth from 2010 through 2019. Manhattan's quality-adjusted net effective rents show a sharp decline in the pandemic-era, with the index barely recovering to its pre-pandemic level by mid-2025. Dallas's office rent trajectory remains relatively stable, with modest increases in the post-COVID period followed by a recent decline. San Francisco stands out for its pronounced cycle–rapid pre-2020 growth followed by a prolonged decline during and after the pandemic. However, the raw series for San Francisco appears to overstate the depth of the initial decline, while the constant-quality (CQR) model reveals a more gradual adjustment, suggesting that the downturn was amplified by a temporary shift toward lower-quality leases. In contrast, in both Manhattan and Dallas, the raw and hedonic series overstate the strength of the post-pandemic recovery, reflecting compositional shifts toward higher-quality leases rather than genuine market rebounds. In the few quarters of our sample (2025.Q2 and Q3), the CQR index for Manhattan points to a recovery while the downturn in San Francisco continues and that in Dallas accelerates. In general, the CQR results underscore how adjustment for lease quality can dampen both exaggerated declines and overstated recoveries, providing a more accurate view of underlying market movements across office markets.

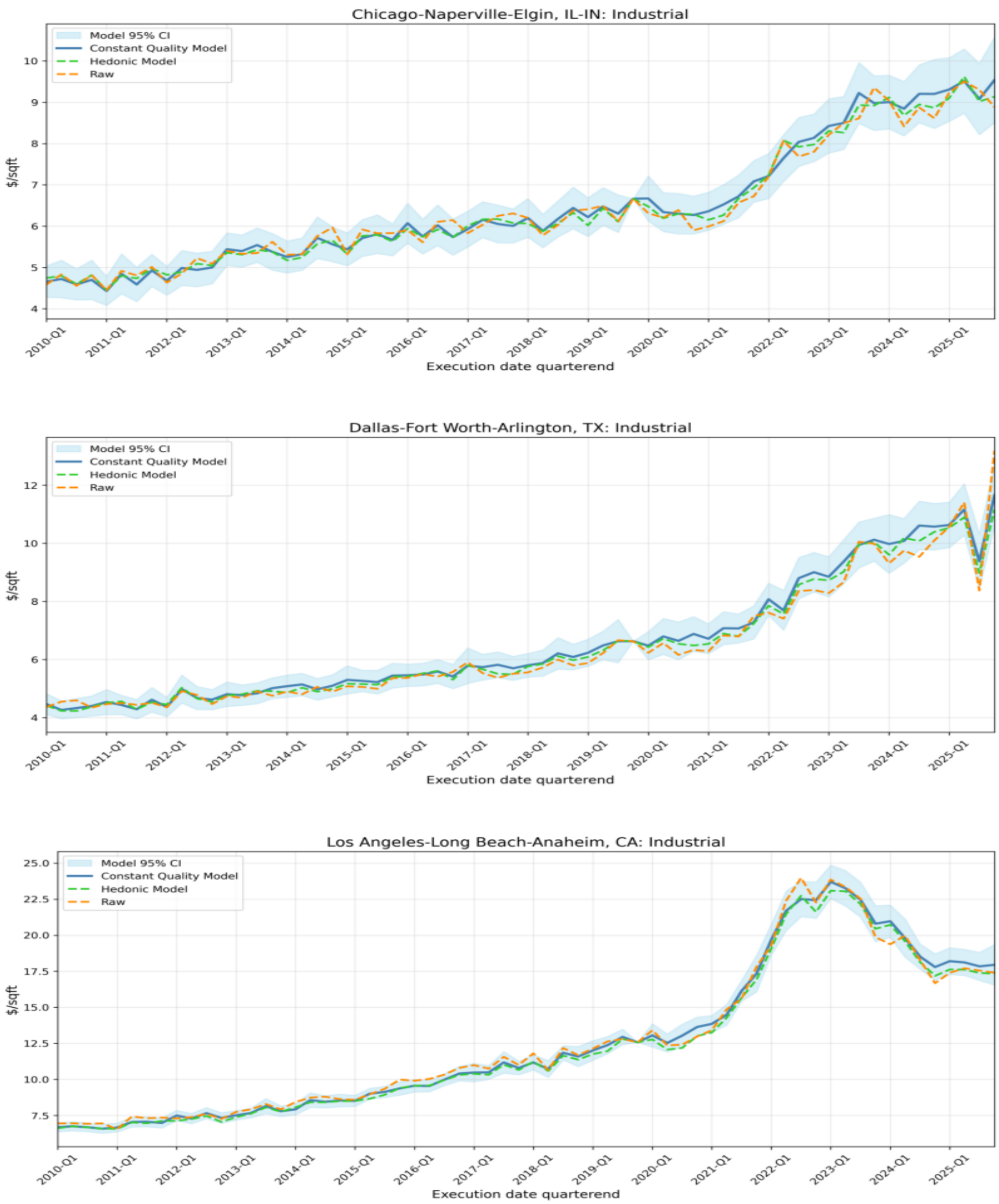
Figure 3 shows that the constant-quality index continues to closely track the hedonic index across the three representative industrial markets: Chicago, Dallas-Fort Worth, and Los Angeles, reflecting the relatively high degree of structural uniformity in this sector. All markets show a pronounced rent acceleration beginning in 2020, reaching a peak in 2022, followed by varying degrees of correction. The pullback is most noticeable in Los Angeles, while Chicago and Dallas exhibit softer adjustments with rents stabilizing near their peaks. Both the constant-quality and the hedonic indices capture this surge and correction, though the

Figure 2: Net Effective Rent of Top 3 Cities in the Office Sector



constant-quality adjusted index presents a smoother, less volatile trajectory compared to the raw data and the simpler hedonic index. This pattern suggests that some of the sharpness in the raw and hedonic series arises from composition effects during the boom period, when new facilities disproportionately influenced transaction data.

Figure 3: Net Effective Rent of Top 3 MSAs in the Industrial Sector



Retail rents in Figure 4 exhibit markedly different behavior when controlling for quality compared to the raw series. In all three representative markets–Manhattan, San Francisco, and Dallas–nominal rents display high volatility with no clear upward trend. The constant-quality index in Manhattan oscillates between roughly 125 and 225 dollars per square foot, peaking in 2016, while the raw and hedonic series show large quarter-to-quarter swings, sometimes exceeding 50 dollars per square foot. This volatility in the raw data, similar to that observed in the national retail index, reflects compositional shifts rather than genuine market movements. While noisy, these trends suggest a modest recovery of retail leases in Manhattan from a pandemic dip, with rents in San Francisco remaining somewhat below their pre-pandemic levels, resembling the patterns seen in office markets across these locations. Mirroring the office market trends in Dallas, the city's quality-adjusted retail rents do not exhibit a pronounced decline during the pandemic.

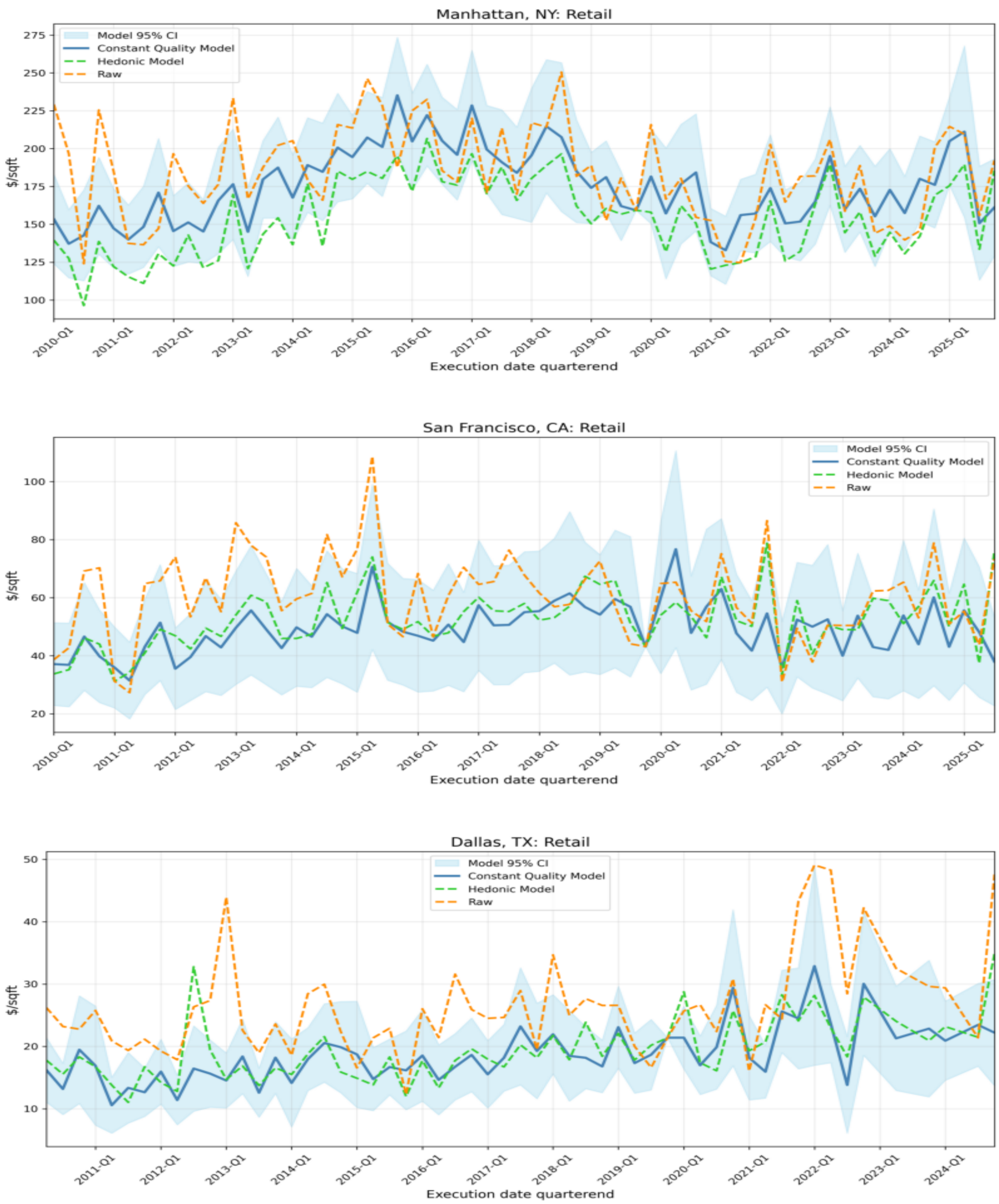
Starting Rents and Concessions Our main rent index studies the net effective rent. To better understand the components underlying this measure, we also analyze the log of starting (or taking) rents, tenant improvements (as a percent of contract value), and free rent (as a percent of lease duration) as dependent variables. These elements, which jointly determine the net effective rent, are of independent analytical interest, as they reveal the different margins along which landlords compete for tenants. As a case study, we use the Manhattan office market to illustrate how each of these margins has evolved over time.

Figures 5–7 investigate Manhattan office space on the basis of starting rent, tenant-improvements, and free-rent concessions. Starting rents (Figure 5) closely mirror the net effective rent series, and reflect a similar benefit from a quality-adjustment. Tenant-improvements (Figure 6) exhibit a clear upward drift from 6 to 12% of total lease value over the sample period. Constant-quality tenant improvements tend to be above the raw averages in the post-pandemic period. This is consistent with above-average quality buildings offering lower TIs than below-average quality leases. A benefit from our quality-adjustment is that it filters out large spikes, such as the spike in TI we see in the raw and hedonic index in 2018.Q2.

Free rent concessions (Figure 7) expanded markedly over the sample period, rising from roughly 4% to 9% of the lease term between 2010 and 2022, before falling back to 8% at the end of 2025.Q3. The increased acceleration during the pandemic years perhaps reflects the heightened use of non-price incentives to maintain office occupancy rates. Both the hedonic and constant-quality models track this trend closely, but the constant-quality index does not exhibit the transitory declines seen in the raw and hedonic series between 2020 and 2023. The fact that concessions under the CQR model remain above the raw averages suggests that bargaining power may still lie with tenants, at least for the average Manhattan office lease.

Time-Varying Hedonic Prices Given the profound disruptions caused by COVID-19, it is natural to consider that the implicit prices of key characteristics may have shifted during this period. To examine potential structural changes in the valuation of lease and building attributes around the pandemic, and to assess the robustness of our results, we extend our CQR framework to allow the hedonic coefficients to vary across

Figure 4: Net Effective Rent of Top 3 MSAs in the Retail Sector



the pre- and post-COVID periods. To implement this, we estimate the following model:

$$\log Y_{ijmst} = \alpha_{mst} + HGFE_j + \beta^{pre} X_{ijmst} + \beta^{covid} \left(X_{ijmst} \cdot 1\{\text{t} > \text{2020.Q1}\}_t \right) + \epsilon_{ijmst} \tag{5}$$

We present the regression estimates of the national analog of this specification in Table A.11 across the

Figure 5: Starting Rents Manhattan Office Market

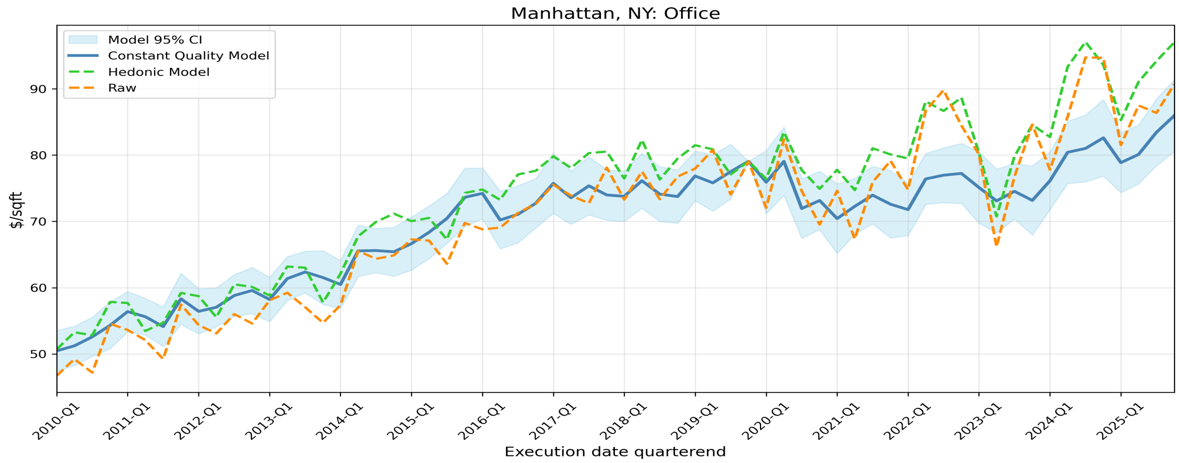


Figure 6: Tenant Improvements Manhattan Office Market

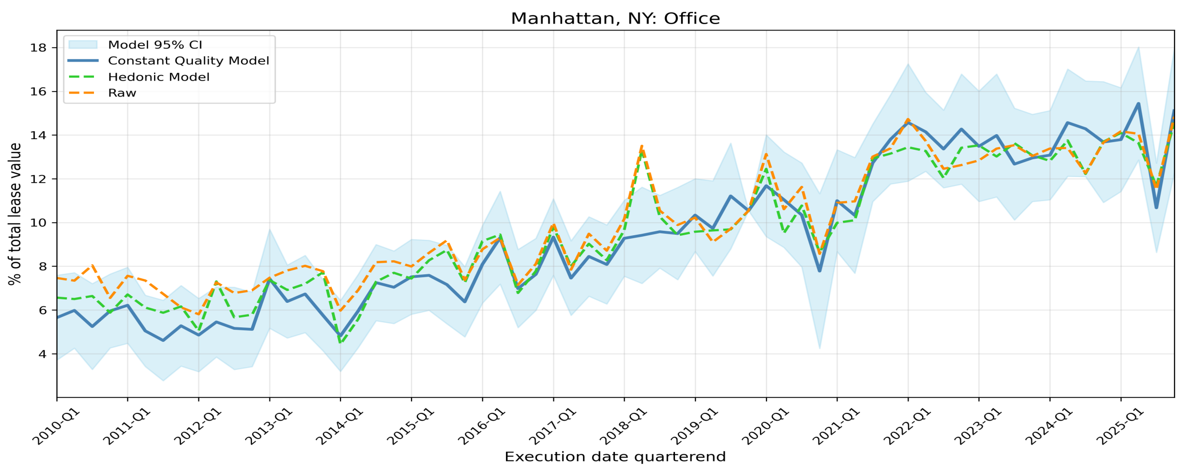
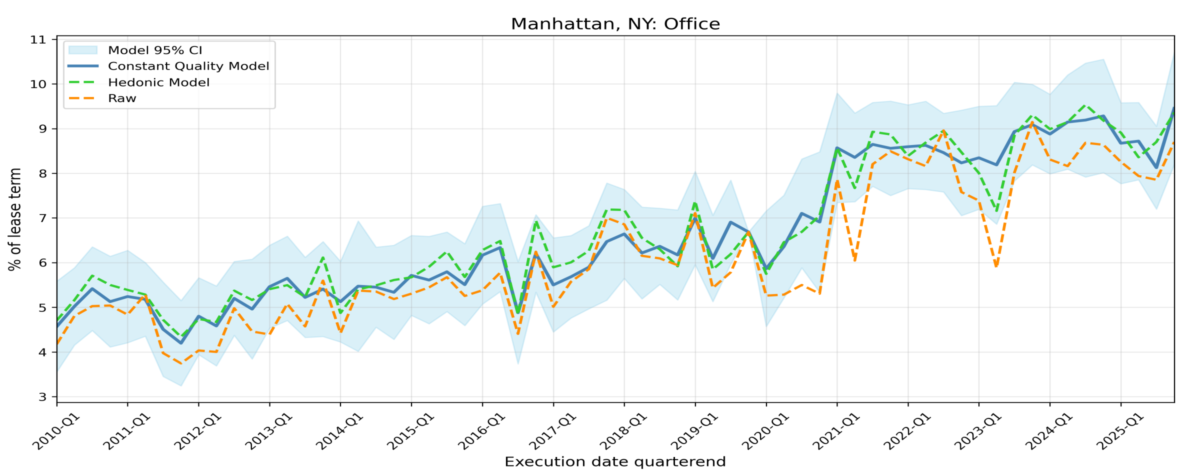


Figure 7: Free Rent Manhattan Office Market



three space types. It reports a larger discount for older properties post covid, especially for office and to a lesser extent also for retail, whereas the reverse is true for industrial. The post-covid era reduces the CBD rent premium for office and reverses it for retail, but not for industrial. The rent premium for longer-term leases weakens during this period in office but not in industrial. The importance of clearing height in industrial increases with the growth of robotics-enabled warehouses.

While there are meaningful differences in hedonic prices post-covid, the resulting national CQR indices track the baseline indices closely, as shown in Figure A.1. Directionally, the model that allows for post-covid coefficient changes results in even more modest rent growth post–2020 in office and industrial, reinforcing our conclusion. The reverse is true for retail. Figure A.2 quantifies the difference between the MSA-level rent indices resulting from the baseline CQR model in (1) and the alternative CQR model in (5), as the RMSE between the two series. For office and industrial MSAs, most RMSE values cluster tightly below 0.2. The difference is a little larger for the retail sector, with most MSAs showing differences below 0.5. In summary, allowing for post-COVID coefficient changes has relatively modest effects on aggregate rent dynamics.

Where Quality-Adjustment Matters Most We next examine where quality adjustment matters most across markets. Table 3 summarizes the five markets in each sector with the largest root-mean-squared deviation between the constant-quality and raw rent indices. Only markets with at least 32 quarters of estimates are considered. The largest gaps occur in heterogeneous smaller office and retail markets like Tempe, AZ and Jacksonville, FL, where leasing activity spans diverse asset classes and fluctuates sharply over time. In these markets, the raw index tends to overstate volatility because of the changing mix of transacting properties every quarter instead of true shifts in market rents. The CQR model filters out this compositional noise by holding building quality fixed, yielding a more interpretable rent path. Industrial markets on the other hand showcase much smaller RMSE values. This is partly due to fewer idiosyncratic property attributes contributing to prices, meaning that the raw and quality adjusted series move closely. Overall, the RMSE patterns confirm that the constant-quality model delivers its greatest improvements in smaller, higher-variance markets where unobserved heterogeneity is severe, while being similar to the raw data where the properties are more uniform.

Table 3: Top 5 Locations by RMSE Between CQR and Raw Indices

Office (City)		**Office (MSA)**	
Location	RMSE	Location	RMSE
Tempe, AZ	0.367	Fresno, CA	0.283
Culver City, CA	0.367	Greenville-Anderson-Greer, SC	0.252
Henderson, NV	0.363	Charleston-North Charleston, SC	0.216
Fort Lauderdale, FL	0.295	Bridgeport-Stamford-Danbury, CT	0.215
Menlo Park, CA	0.291	Birmingham, AL	0.209

Retail (City)		**Retail (MSA)**	
Location	RMSE	Location	RMSE
Jacksonville, FL	0.792	Jacksonville, FL	0.792
Indianapolis, IN	0.711	Boise City, ID	0.724
Miami, FL	0.623	Greenville-Anderson-Greer, SC	0.700
Salt Lake City, UT	0.529	Indianapolis-Carmel-Greenwood, IN	0.639
Tampa, FL	0.523	Birmingham, AL	0.610

Industrial (MSA$_FE$)	
Location	RMSE
Ogden, UT	0.299
San Francisco-Oakland-Fremont, CA	0.251
Boston-Cambridge-Newton, MA-NH	0.234
Kansas City, MO-KS	0.217
Oklahoma City, OK	0.216

6 Discussion

6.1 The Economic Content of CQR Indices

The Relationship between National and Local Indices Having estimated CQR indices for many markets, we are interested in studying the degree of comovement between markets. To what extent are rent dynamics in, say, local office markets driven by the national office market dynamics or rather by market-specific forces. We develop measures of regional integration.

To match the quarterly frequency of the market-level CQR indices, we construct a quarterly national CQR index. We then estimate the following OLS regressions for each space type s and market m:

$$\alpha_{m,s,t} \quad = \quad c_m^L \; + \; \beta_m^L \, \alpha_{s,t} \; + \; \varepsilon_{m,s,t}^L \tag{6}$$

$$\alpha_{m,s,t} - \alpha_{m,s,t-4} \quad = \quad c_m^G \; + \; \beta_m^G \; (\alpha_{s,t} - \alpha_{s,t-4}) \; + \; \varepsilon_{m,s,t}^G, \tag{7}$$

where the first specification studies the relationship between the national CQR index and market CQR index in levels and the second one in year-over-year growth rates. The coefficient β_m^L (β_m^G) captures the elasticity of local rent levels (growth rates) with respect to national rent levels (growth rates), while the regression R^2 measures the share of variation in local rent (growth) movements explained by the national factor.

We estimate (6) and (7) for each MSA with at least 32 CQR estimates. The results in Panel A of Table 4 indicate that, on average, national rent movements explain a large share of local rent movements in levels. The median elasticity coefficient β_m^L is around 1 and the median R^2 ranges from 60% for office, 36.5% for retail, to 91% for industrial. There is clearly a strong common factor in industrial rents across the country. Industrial rents were trending up in most markets. Office and retail rents do not display a clear trend, and are more heterogeneous across markets. Nevertheless, there is still a sizeable common component in local office and retail rent levels.

Turning to the relationship between annual growth rates in Panel B, we see that national rent growth only explains a small share of the variation in local rent growth rates. The median elasticity coefficient β_m^G is around 0.7, lower than the sensitivity in levels. In the office and retail markets, the median R^2 is only around 3-4%. It is 15% for industrial rent growth. These results suggest that idiosyncratic local dynamics dominate national movements and that there are great gains from geographic diversification, at least in terms of rent growth fundamentals. The higher R^2 for industrial again points to more commonality in industrial rent growth rates across MSAs than there is in the office and retail markets. This is consistent with the discussion in Section 5, which noted that industrial markets exhibit a higher degree of structural homogeneity and cross-market integration than office or retail sectors.

Table 4: National Variation in Local Indices: Level vs Growth

	Panel A: Levels			Panel B: Growth Rates		
Space Type	Median Beta	Median R^2	Median N Obs	Median Beta	Median R^2	Median N Obs
Office	0.934	0.598	63.5	0.491	0.029	60.0
Retail	1.156	0.365	57.0	0.710	0.039	54.0
Industrial	0.932	0.907	63.0	0.808	0.152	59.5

Next, we study how the comovement between local rents has evolved over time, inspired by an analysis in Kallberg, Liu and Pasquariello (2014) that shows increasing integration of housing markets in the aftermath of the Great Financial Crisis. To do so, we estimate sliding 20-quarter fixed-window versions of (6) and (7). The first estimates are for the period 2016.Q1, the last estimates for 2025.Q4. We then compute the cross-sectional median of slope coefficient and R^2 estimates to assess whether the extent of regional integration has increased or decreased over time. We find that the patterns of integration differ substantially across property types. Figure 8 summarizes the evidence.

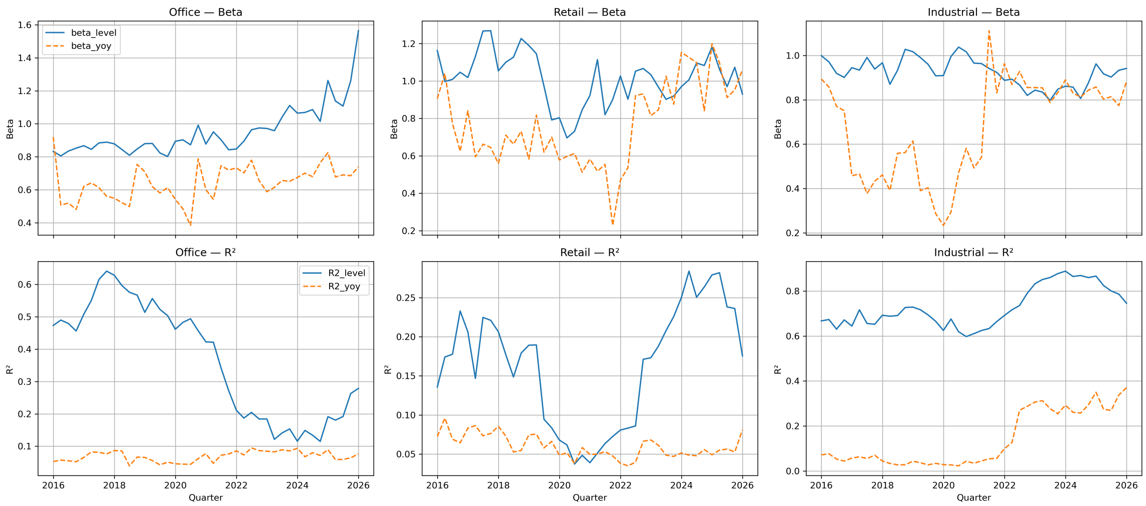
For Industrial (right panels), the median rolling R^2 exhibits a clear upward trend, indicating that national fundamentals explain an increasing share of MSA-level variation post-pandemic. The median sensitivity in levels (β_m^L) does not show an increase, while the sensitivity in growth rates (β_m^G) increases earlier. This pattern suggests rising national integration in explanatory power rather than in sensitivity.

Office markets show the opposite pattern (left panels). While the rolling level betas increase sharply around the COVID-19 shock–consistent with a heightened directional sensitivity to national conditions–the median R^2 simultaneously collapses.[3] This combination points to a growing importance of local idiosyncratic variation: office markets move in the same broad direction as the national sector, but local shock volatilities have increased so much that national fundamentals explain a shrinking fraction of total variance. Indeed, the COVID-19 pandemic and the ensuing adoption of work from home led to a nationwide office apocalypse (Gupta, Mittal and Van Nieuwerburgh, 2025). The recovery since then has been uneven, with markets such as Manhattan performing much better than markets like Seattle or Chicago.

Retail lies between these two extremes. The rolling betas rise modestly in the post-COVID period. The R^2 series shows a substantial decrease before 2020 and a sharp increase after 2021. The 2010–15 period saw the widespread adoption of e-commerce, which hit all retail markets hard, resulting in high β_m^L and R^2. What followed in 2016–20 was a period of market bifurcation with winners and losers (β_m^L and R^2). The 2021–25 period saw a return of the importance of national consumer and retail cycles as the key drivers of local retail rents.

[3] Time-trend regressions confirm that the post-COVID period is characterized by rising betas but falling explanatory power.

Figure 8: Rolling Comovement Between MSA and National CQR by Property Type



Notes: This figure reports 20-quarter rolling window regressions of MSA-level log CQR indices on the corresponding national log CQR indices, separately for Office, Retail, and Industrial space. The top row plots the rolling regression coefficients for levels (solid lines) and year-over-year changes (dashed lines). The bottom row plots the corresponding coefficients of R^2. For each quarter and property type, the curves show the cross-sectional median across MSAs.

Local Macroeconomic Variables We relate the growth rate in our CQR rent indices at the MSA level to the following 5 local macroeconomic indicators. Local employment growth and growth in personal income per capita are sourced from the Bureau of Economic Analysis (BEA) at the FIPS level and aggregated to the MSA level; they are both available at annual frequency. Occupancy rate changes and net operating income (NOI) growth[4] are obtained from NCREIF[5]; the occupancy rate is reported at quarterly frequency, while NOI growth is annual, and both are measured at the MSA level. We also correlate our commercial rent growth measure with residential rent growth obtained from Zillow at the MSA level. We use the ZORI all properties index, which includes both single- and multi-family rental properties. We average the original monthly series across the months within the quarter and compute a quarterly growth rate from the log differences.

Our baseline outcome variable is the growth rate of our CQR commercial rent index at the MSA level. The CQR indices are constructed at a quarterly frequency. When relating them to quarterly macro variables, we use quarter-on-quarter log changes. When relating them to annual variables (such as employment growth, income growth, and NOI growth), we instead construct an annual rent growth measure defined as the log difference between the last quarter of year t and the last quarter of year $t-1$. For comparison, we apply the same transformation to the raw average rent levels to assess whether our CQR series strength-

[4]NOI is the standard cash-flow measure in commercial real estate, computed as rent revenues minus operating expenses.

[5]The National Council for Real Estate Investment Fiduciaries (NCREIF) is a consortium of large institutional real estate investors that share detailed portfolio data, allowing the construction of market-level cash-flow and occupancy statistics. We thank NCREIF for making these data available to us.

ens or weakens the correlation with local macroeconomic conditions relative to the unadjusted data. In addition to estimating separate regressions for each macro variable, we also estimate a joint specification that includes all five indicators simultaneously; in this case, quarterly rent growth is converted to its annual counterpart, also using the last quarter of year t and the last quarter of year $t-1$, to ensure consistent alignment across variables. We estimate the following regression for each space type s and market m:

$$\Delta \log R^{(k)}_{m,s,t} \;=\; c^{(k)}_s \;+\; \beta^{(k)}_s \, X_{m,s,t} \;+\; \varepsilon^{(k)}_{m,s,t}, \tag{8}$$

where $\Delta \log R^{(k)}_{m,s,t}$ denotes the (quarterly or annual) log rent growth in MSA m and period t for index type $k \in \{\text{raw}, \text{CQR}\}$, and $X_{m,s,t}$ stands either for a single macroeconomic indicator or, in the joint specification, the full set of local fundamentals (NOI growth, employment growth, income growth, occupancy rate changes, and ZORI rent growth). For the CQR model, $\Delta \log R^{(k)}_{m,s,t} = \Delta\alpha^{(k)}_{m,s,t}$.

Table 5 Panel A reports the results for industrial properties. Industrial rent growth is strongly positively correlated with local employment growth, both for our CQR index and raw rents, underscoring the cyclical pattern of industrial real estate. Our CQR measure of industrial rent growth also has a marginally significant sensitivity to residential rent growth of around 30% while the raw measure has a marginally significant sensitivity to income growth.

In the joint specifications that include all macro variables simultaneously, employment growth is the only robust driver of industrial rent growth in both the CQR and raw series. NOI growth enters significantly in column (6).

Table 5 Panel B presents the results for office markets. As in the industrial sector, employment growth is consistently significant across CQR and raw, with positive coefficients in both the raw and CQR regressions. The sensitivity of office rent to employment growth is about 40% smaller for office than for industrial according to our measure, whereas the sensitivity of the raw rent growth series is broadly similar.

When all macro variables enter together, the CQR index continues to load mainly on employment growth. By contrast, the raw index produces additional significant coefficients, which indicate that these effects are driven by shared variation or composition noise rather than genuine underlying fundamentals. The CQR specification therefore delivers a cleaner and more stable pattern of partial correlations for office markets.

An interesting pattern across the results is the role of per capita income growth in the office and industrial sectors. While income growth is positively and significantly correlated with raw rent growth, this relationship disappears for the CQR series. This suggests that the significant positive association in the raw data is likely driven by sample-composition effects. In particular, periods with strong local income growth may coincide with a greater share of high-quality transacted assets in the raw sample, mechanically inflating measured rent growth. After the CQR procedure removes these quality-related compositional shifts, the correlation between income growth and commercial rent growth vanishes.

Table 5 Panel C summarizes the results for retail properties. In this sector, occupancy rate changes are individually significant. In the joint model, none are significant in column (6).

Within-Market Cross-Sector Correlation For each MSA, we compute pairwise correlations between the time series of Office, Retail, and Industrial CQR index levels, for periods where each sector-pair is non-missing. The resulting correlations are then averaged across MSAs. The cross-market means indicate substantial co-movement across sectors, with an overall average correlation of 0.49. Office-Retail, Office-Industrial, and Retail-Industrial correlations average approximately 0.44, 0.68, and 0.55, respectively. Rent levels tend to move together across property types within local markets.

Nominal vs Real Indices So far, we have studied nominal CQR indices. Since real estate is often thought to provide inflation-protected cash flows, we also construct real CQR indices. To do so, we deflate the nominal CQR index by the local consumer price index, obtained from the Bureau of Labor Statistics. MSA-level CPI indices are available for 14 MSAs. For the remainder, we assign the national CPI index. Cumulative inflation between 2019.Q3 and 2025.Q3 is as low as 20.8% in San Francisco-Oakland-Fremont, CA and as high as 32.1% in Miami-Fort Lauderdale-West Palm Beach, FL. Nationally, cumulative inflation was 26.2% over this period. Nominal rent growth is significantly positively correlated with local inflation in the Industrial and Retail sectors. In Industrial, a panel regression of MSA-level nominal rent growth on inflation shows a significant coefficient of 1.68 and an R^2 of 6.2%. In Retail, the coefficient on inflation is 0.9 and the R^2 is 0.6%. Office rents show a much lower and statistically insignificant relationship of 0.3 (R^2 of 0.2%). We conclude that Industrial CRE has offered a strong inflation hedge over the past fifteen years. Retail offered partial inflation protection but the connection between local purchasing power and local retail rents was weak. Office rents failed to keep up with inflation and seemed disconnected from local inflation. While office rents grew by 5.8% nationally over the six years between 2019.Q3 and 2025.Q3, they fell by 16.2% in real terms.

Table 5: Regressions of rent growth on macro variables

	CQR Index Growth						Raw Rent Growth					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Industrial												
NOI growth	0.076					0.142**	0.105					0.119
	(0.179)					(0.047)	(0.174)					(0.224)
Employment growth		0.951***				0.938***		1.198***				1.526***
		(0.000)				(0.005)		(0.000)				(0.001)
Income growth			0.200			-0.232			0.533*			0.611
			(0.311)			(0.463)			(0.063)			(0.161)
Occupancy rate change				-0.049		0.085				-0.177		0.065
				(0.593)		(0.678)				(0.160)		(0.818)
ZORI rent growth					0.302*	0.259					0.265	-0.196
					(0.072)	(0.237)					(0.254)	(0.515)
Observations	390	560	560	1482	1900	236	390	560	560	1482	1900	236
R-squared	0.005	0.030	0.002	0.000	0.002	0.075	0.005	0.023	0.006	0.001	0.001	0.061
Panel B: Office												
NOI growth	0.021					0.021	0.023					-0.095
	(0.622)					(0.713)	(0.772)					(0.448)
Employment growth		0.567***				0.677*		1.276***				1.605**
		(0.007)				(0.053)		(0.000)				(0.036)
Income growth			0.013			0.403			0.661**			1.654**
			(0.940)			(0.214)			(0.027)			(0.020)
Occupancy rate change				-0.018		-0.008				-0.140		0.858***
				(0.834)		(0.956)				(0.342)		(0.008)
ZORI rent growth					-0.144	-0.043					-0.073	-0.276
					(0.384)	(0.847)					(0.782)	(0.570)
Observations	368	649	649	1402	2247	215	368	649	649	1402	2247	215
R-squared	0.001	0.011	0.000	0.000	0.000	0.031	0.000	0.019	0.008	0.001	0.000	0.084
Panel C: Retail												
NOI growth	0.132					0.221	0.149					0.391
	(0.201)					(0.134)	(0.414)					(0.112)
Employment growth		0.478				-0.819		-0.194				-3.160**
		(0.257)				(0.282)		(0.786)				(0.013)
Income growth			0.151			-0.231			-0.157			-1.644
			(0.666)			(0.742)			(0.791)			(0.162)
Occupancy rate change				0.343*		-0.141				0.338		0.192
				(0.060)		(0.612)				(0.284)		(0.679)
ZORI rent growth					0.201	0.327					-0.458	1.016
					(0.509)	(0.482)					(0.380)	(0.192)
Observations	346	602	602	1274	2097	219	346	602	602	1274	2097	219
R-squared	0.005	0.002	0.000	0.003	0.000	0.015	0.002	0.000	0.000	0.001	0.000	0.038

6.2 Robustness: Flexible Functional Forms for Covariates

General Additive Model Our baseline CQR framework imposes a linear structure on the relationship between log net effective rents and lease and property characteristics, several of which are expressed in logs. As a robustness check, we now allow for a more flexible functional form for the characteristics vector $f(X_{ijt})$. Specifically, our general additive model includes cubic splines of the continuous feature variables. The resulting CQR index for this exercise is plotted in Figure A.3, alongside our baseline CQR index. In the presence of high-dimensional HGFE, allowing for non-linearities in the lease and property covariates results in negligible changes to our linear index.

Machine Learning We can go a step beyond the general additive model to allow for a more general non-parametric relationship between rents and the control variables. We start from net effective rents rather than logs of net effective rent. We consider generic non-linearities of the controls as well as interaction effects between the control variables in X_{ij}. First, this flexibility could allow us to capture complex non-linearities that may be missed by the log-linear specification such as diminishing returns to building size, or interactions such as differential effects from lease term across building classes. Second, this exercise provides a robustness check on the validity of the linear hedonic structure. If the more flexible model yields only modest improvements in predictive accuracy, it suggests that the original linear CQR model is sufficient to accurately describe the panel of rent data. On account of its ease of interpretation and parsimony, it should be preferred to the machine learning model.

Our machine-learning algorithm proceeds in two steps. First, we use Light Gradient Boosted Machine (LGBM), a tree-based ML model, to fit a flexible relationship between the NER and the covariates:

$$\hat{R}_{ijst} = \hat{f}(X_{ijst}) \tag{9}$$

Second, we form the prediction residuals from step 1, $\tilde{R}_{ijst} = R_{ijst} - \hat{R}_{ijst}$, which capture the component of observed rents R_{ijst} that is unexplained by the control function $\hat{f}(\cdot)$, and estimate an OLS panel regression of these unexplained rents on time FEs and HGFEs:

$$\tilde{R}_{ijst} = \alpha_{st} + HGFE_j + \epsilon_{ijst} \tag{10}$$

The LGBM model is limited to a maximum tree depth of 5 and undergoes 5-fold cross validation to ward off overfitting concerns common in machine learning model estimation.

The estimates α_{st} are converted to an index as in (2) and (4). Figure A.4 compares the indices obtained from the benchmark CQR and the LGBM model for the national and the Manhattan office space markets and Figure A.5 plots the distribution of the RMSE differences across MSAs. The differences between the benchmark model and the LGBM CQR indices are generally small, and reinforce the conclusions we drew from the GAM plotted in Figure A.3.

7 Conclusion

This paper develops a new quality-adjusted commercial real estate rent index for the U.S. office, retail, and industrial sectors using a large, nationally representative dataset of CompStak leases from 2010–2025. By combining a rich hedonic specification with hierarchical geographic fixed effects, our framework isolates underlying rent dynamics from shifts in the composition of transacting properties, thereby correcting the substantial biases embedded in raw and simple hedonic rent series. Across sectors, we show that composition effects are economically meaningful. Office and retail rents exhibit notably weaker post-pandemic recoveries once quality is held constant, while industrial rents display only modest distortions, reflecting the sector's relative homogeneity.

Local indices further reveal the highly uneven nature of commercial rent adjustments, with pronounced pandemic-era declines in markets such as San Francisco and only modest recoveries in Manhattan. These patterns underscore the importance of controlling for latent quality differences when comparing markets or evaluating cyclical turning points. Our analysis of starting rents, tenant improvements, and free-rent concessions shows that non-price margins have played an increasingly important role over the sample period, especially in the post-COVID office market. Finally, we document substantial variation in regional integration across sectors, with industrial markets becoming more synchronized nationally and office markets showing rising local idiosyncrasy.

Overall, the CQR indices provide a transparent, empirically grounded measure of commercial rent fundamentals, improving inference for researchers, policymakers, and market participants. By correcting for quality-driven composition effects, our framework offers a more accurate lens through which to evaluate commercial real estate performance and its connection to broader economic conditions.

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Appendix

A Market Definition

We estimate indices for markets across the office, retail, and industrial sectors. Our starting universe is the set of all U.S. metropolitan and micropolitan statistical areas (MSAs) that appear in our raw data, totaling 920 distinct MSAs as defined by the U.S. Office of Management and Budget.

To include a market in our estimation, we impose a minimum data-density requirement. A market must have at least five observations in a given quarter, with no more than five quarters falling below this threshold over the entire estimation window. The estimation period for each market is defined as the longest continuous span that (1) begins in 2010 or later, (2) extends through the most recent quarter (i.e., 2025Q2 must contain at least five observations[6]) and (3) has its first quarter starting before 2018. These criteria ensure sufficient data coverage and minimize discontinuities while retaining the maximum feasible time series for each market. Applying these criteria yields 56 eligible MSAs for industrial, 76 for office, and 84 for retail. After imposing additional degrees-of-freedom requirements in the regression stage, the final estimation sample comprises 49 industrial MSAs, 61 office MSAs, and 66 retail MSAs.

For all three sectors, we construct indices at the MSA level, using all leases that fall within each MSA as defined above. For the office and retail sectors, we additionally estimate indices at the city level for all cities that satisfy the same data requirements. City-level markets are defined using CompStak's city designations, and city-level indices are estimated alongside rather than as a substitute for, their corresponding MSA-level indices: a city that meets the sample thresholds appears both as its own city-level market and as part of the broader MSA market.

In addition to standard MSAs and cities, we construct a small set of special geographic markets that aggregate leases into economically meaningful areas that do not map cleanly into a single MSA or municipal boundary. These special markets are based on CBRE's market definitions and include, for example, New York City's outer boroughs, the Inland Empire in Southern California, and New Jersey. For each such geography, we follow the same data filters and estimation rules described above, treating these aggregates as additional markets for which we estimate indices.

A.1 List of Cities

Office Alexandria, VA; Aliso Viejo, CA; Alpharetta, GA; Arlington, VA; Atlanta, GA; Austin, TX; Baltimore, MD; Baton Rouge, LA; Beaverton, OR; Bellevue, WA; Bethesda, MD; Beverly Hills, CA; Boca Raton, FL; Boise, ID; Boston, MA; Campbell, CA; Carlsbad, CA; Centennial, CO; Century City, CA; Chandler, AZ; Chantilly, VA; Charlotte, NC; Chicago, IL; Clearwater, FL; Colorado Springs, CO; Concord, CA; Culver City, CA; Cupertino, CA; Dallas, TX; Denver, CO; Doral, FL; Duluth, GA; Durham, NC; El Segundo, CA; Englewood, CO; Fairfax, VA; Falls Church, VA; Folsom, CA; Fort Lauderdale, FL; Fremont, CA; Gaithersburg, MD; Glendale, CA; Greenville, SC; Greenwood Village, CO; Henderson, NV; Herndon, VA; Houston, TX; Indianapolis, IN; Irvine, CA; Jacksonville, FL; Kansas City, MO; La Jolla, CA; Las Vegas, NV; Lehi, UT; Lisle, IL; Long Beach, CA; Los Angeles, CA; Los Gatos, CA; Manhattan, NY; Marietta, GA; McLean, VA; Menlo Park, CA; Mesa, AZ; Miami, FL; Milpitas, CA; Minneapolis, MN; Mountain View, CA; Murray, UT;

[6] Although some data are available for 2025Q3, coverage is incomplete, so we apply the five-observation requirement to 2025Q2 when screening markets.

Naperville, IL; Nashville, TN; New York City Outer Boroughs; Newport Beach, CA; Norcross, GA; Oak Brook, IL; Oakland, CA; Oklahoma City, OK; Orange, CA; Orlando, FL; Overland Park, KS; Palo Alto, CA; Pasadena, CA; Phoenix, AZ; Pittsburgh, PA; Plano, TX; Pleasanton, CA; Portland, OR; Princeton, NJ; Raleigh, NC; Rancho Cordova, CA; Redwood City, CA; Reston, VA; Rockville, MD; Roseville, CA; Sacramento, CA; Salt Lake City, UT; San Antonio, TX; San Diego, CA; San Francisco, CA; San Jose, CA; San Mateo, CA; Santa Ana, CA; Santa Clara, CA; Santa Monica, CA; Schaumburg, IL; Scottsdale, AZ; Seattle, WA; Sugar Land, TX; Sunnyvale, CA; Tampa, FL; Tempe, AZ; Torrance, CA; Tucson, AZ; Vienna, VA; Walnut Creek, CA; Washington, DC; West Hollywood, CA; Westlake Village, CA; Woodland Hills, CA.

Retail Albuquerque, NM; Atlanta, GA; Austin, TX; Boise, ID; Charlotte, NC; Chicago, IL; Columbus, OH; Dallas, TX; Fort Worth, TX; Glendale, AZ; Houston, TX; Indianapolis, IN; Jacksonville, FL; Kansas City, MO; Las Vegas, NV; Long Beach, CA; Los Angeles, CA; Manhattan, NY; Mesa, AZ; Miami, FL; New York City Outer Boroughs; Oakland, CA; Orlando, FL; Overland Park, KS; Phoenix, AZ; Pittsburgh, PA; Portland, OR; Raleigh, NC; Sacramento, CA; Salt Lake City, UT; San Antonio, TX; San Diego, CA; San Francisco, CA; San Jose, CA; Scottsdale, AZ; Seattle, WA; Tampa, FL; Tucson, AZ; Washington, DC. .

A.2 Special geographic markets

Inland Empire (CA): Banning; Beaumont; Colton; Corona; Norco; Moreno Valley; Perris; Redlands; Loma Linda; Rialto; Bloomington; Riverside; San Bernardino; Chino; Chino Hills; Fontana; Jurupa Valley; Eastvale; Ontario; Montclair; Upland; Rancho Cucamonga; Adelanto; Apple Valley; Barstow; Hesperia; Victorville; Pomona; Mentone; Highland; Grand Terrace; Yucaipa; Daggett; Indio; Palm Desert; Palm Springs; Cathedral City; Coachella; Thousand Palms; La Quinta; Thermal; Desert Hot Springs; Bermuda Dunes; North Palm Springs; Wildomar; Murrieta; Menifee; Lake Elsinore; Canyon Lake; San Jacinto; Hemet; Calimesa; March Air Reserve Base; Mira Loma; Temecula; Indian Wells; Claremont; San Dimas; La Verne; Covina.

NYC Outer Boroughs (NY): Bronx; The Bronx; Brookyln; Park Slope; Queens; Flushing; Jamaica; Woodside; Maspeth; Long Island City; Richmond Hill; College Point; Middle Village; Forest Hills; Ozone Park; South Ozone Park; Corona; Glendale; Fresh Meadows; Astoria; East Elmhurst; Springfield Gardens; Rego Park; Jackson Heights; Kew Gardens; Elmhurst; Sunnyside; Whitestone; Little Neck; Bayside; Bayside Hills; Saint Albans; Queens Village; Hollis; Rosedale; Howard Beach; Broad Channel; Woodhaven; Laurelton; South Richmond Hill; Arverne; Far Rockaway; Rockaway Beach; Rockaway Park; Kew Gardens Hills; Auburndale; Glen Oaks; Staten Island.

New Jersey : New Jersey State.

Table A.1: Full Sequence from Raw Data to Estimation Sample

Step	Procedure	Leases Remaining (% Raw)
0	Start with raw data	1,208,207 (100.0%)
1	Exclude Land and Other	1,205,264 (99.8%)
2	Remove points mapped to multiple cities	1,204,923 (99.7%)
3	Remove rows without a space type and recode Flex and R&D to Industrial	1,203,832 (99.6%)
4	Remove subleases	1,157,709 (95.8%)
5	Remove rows missing atleast one HGFE level	1,155,223 (95.6%)
6	Remove rows not having atleast 5 observations at any HGFE level	1,155,204 (95.6%)
7	Remove rows with negative lease terms	1,155,199 (95.6%)
8	Remove rows with negative/missing NER	1,128,063 (93.4%)
9	Final estimation sample (2009.Q4 onwards)	895,461 (74.1%)

Note: Summary of the cleaning pipeline. Market filters apply later.

Table A.2: Table A.2: Distribution of Leases by Sector

Sector	Number of Leases	Percentage
Office	492,513	55.00%
Industrial	220,914	24.67%
Retail	182,034	20.33%

Note: This table shows the distribution of leases across sectors in the final estimation sample. Percentages are calculated relative to the total number of leases.

Table A.3: Geographic Distribution: Top 15 MSAs by Number of Leases

MSA	Number of Leases	Percentage
Los Angeles-Long Beach-Anaheim, CA	80,159	8.95%
New York-Newark-Jersey City, NY-NJ	67,189	7.50%
Dallas-Fort Worth-Arlington, TX	61,378	6.85%
San Francisco-Oakland-Fremont, CA	56,095	6.26%
Houston-Pasadena-The Woodlands, TX	42,899	4.79%
Chicago-Naperville-Elgin, IL-IN	42,433	4.74%
Washington-Arlington-Alexandria, DC-VA-MD-WV	40,017	4.47%
Atlanta-Sandy Springs-Roswell, GA	30,370	3.39%
San Jose-Sunnyvale-Santa Clara, CA	27,103	3.03%
San Diego-Chula Vista-Carlsbad, CA	24,032	2.68%
Boston-Cambridge-Newton, MA-NH	23,200	2.59%
Phoenix-Mesa-Chandler, AZ	22,437	2.51%
Denver-Aurora-Centennial, CO	20,867	2.33%
Riverside-San Bernardino-Ontario, CA	18,708	2.09%
Miami-Fort Lauderdale-West Palm Beach, FL	17,644	1.97%

Note: This table shows the top 15 Metropolitan Statistical Areas (MSAs) ranked by the number of leases in the final estimation sample. Percentages are calculated relative to the total number of leases.

Table A.4: Top-10 Markets by Sector

Office Market	Leases	Industrial Market	Leases	Retail Market	Leases
Dallas, TX	29,747	Los Angeles–Long Beach–Anaheim, CA	23,775	New York–Newark–Jersey City, NY–NJ	15,384
Houston, TX	29,591	San Francisco–Oakland–Fremont, CA	14,168	Los Angeles–Long Beach–Anaheim, CA	12,518
Manhattan, NY	26,221	Chicago–Naperville–Elgin, IL–IN	12,645	San Francisco–Oakland–Fremont, CA	8,787
New Jersey	13,460	Inland Empire, CA	11,617	Dallas–Fort Worth–Arlington, TX	7,657
San Francisco, CA	12,582	Dallas–Fort Worth–Arlington, TX	10,687	Chicago–Naperville–Elgin, IL–IN	5,263
Chicago, IL	12,123	San Jose–Sunnyvale–Santa Clara, CA	9,568	Phoenix–Mesa–Chandler, AZ	4,671
Atlanta, GA	11,656	Atlanta–Sandy Springs–Roswell, GA	8,188	Inland Empire, CA	4,366
Washington, DC	10,798	San Diego–Chula Vista–Carlsbad, CA	7,854	Houston–Pasadena–The Woodlands, TX	4,339
Los Angeles, CA	9,559	New Jersey	7,100	Atlanta–Sandy Springs–Roswell, GA	4,153
San Diego, CA	9,064	Tampa–St. Petersburg–Clearwater, FL	5,944	Miami–Fort Lauderdale–West Palm Beach, FL	3,992
All Other	327,712	All Other	109,368	All Other	110,904

Table A.5: Key Variables: Definitions and Coverage in Estimation Sample

Variable	Definition	Observations	Percentage
Log_NER	Log of Net Effective Rent	895,461	100.00%
Starting_Rent	Starting rent per square foot	879,572	98.23%
log_lease_size	Log of lease size (square feet)	895,461	100.00%
log_building_size	Log of building size (square feet)	703,093	78.52%
log_lease_term	Log of lease term (months)	893,678	99.80%
log_renovation_age	Log of renovation-adjusted building age (years)	860,281	96.07%
log_average_floor	Log of average floor occupied by the lease	344,418	38.46%
Lease_Type	Type of lease (e.g., Direct, Sublease)	746,108	83.32%
Transaction_Type	Type of transaction	669,454	74.76%
Tenant_Industry	Industry of the tenant	601,065	67.12%
Building_Class	Building class (A, B, C)	766,914	85.64%
Space_Subtype	Space subtype (e.g., Flex, R&D, etc.)	180,183	20.12%
Building_FE	Building fixed effect identifier	895,461	100.00%
Block_Group_FE	Block fixed effect identifier	895,461	100.00%
CBD_Indicator	Indicator equals to 1 if the building is located in the CBD	895,461	100.00%
Transaction_SQFT	Transaction square footage (used as regression weight)	895,461	100.00%

Note: This table shows the coverage of key variables in the final estimation sample. Percentages are computed as the share of non-missing values relative to total observations.

Table A.6: Top 15 Property Subtypes by Sector

Sector	Office	Retail	Industrial
Subtype	Medical	Fast Food/Quick Service, Restaurant	Distribution, Warehouse
	Flex	Restaurant	Flex
	Life Science	Inline	Manufacturing
	R&D	Freestanding	R&D
	Lab, Life Science	Personal Services	Flex, Warehouse
	Lab, Medical	Health & Fitness Center/Sports Club/Gym	Distribution, Manufacturing, Warehouse
	Personal Services	Medical	Light Industrial
	Freestanding, Medical	Bank	Distribution, Flex, Warehouse
	Lab, Life Science, R&D	Automotive	Automotive
	Life Science, R&D	Big Box	Lab, Life Science
	Showroom	Street/Storefront	Warehouse
	Freestanding	Inline, Personal Services	Life Science
	Flex, Medical	Discount Store	Cold Storage
	Flex, R&D	Drug Store, Medical	Distribution, Light Industrial, Warehouse
	Bank	Grocery Store	Automotive, Distribution, Warehouse
Total Number of Subtypes	25	161	113

Note: This table shows, by frequency (count) within each sector, the top 15 property subtypes (`Space_Subtype`) used as categorical control variables in the hedonic regression analysis. Subtypes are specific classifications of space types within each sector.

Table A.7: Building Class Distribution by Sector

Sector	Class A	Class B	Class C
Office	46.74%	44.71%	8.55%
Retail	26.81%	46.76%	26.42%
Industrial	20.36%	54.03%	25.61%

Note: This table shows the percentage distribution of leases across building quality classes (A, B, C) by sector. Class A buildings represent the highest quality tier, while Class C represents the lowest.

Table A.8: Lease Size Distribution by Sector

Sector	Mean	10%	25%	50%	75%	90%	N
Office	9,073	600	1,413	3,125	7,582	18,876	492,513
Retail	5,608	914	1,300	2,186	4,390	10,640	182,034
Industrial	46,569	2,243	5,000	13,750	40,800	110,756	220,914

Note: Lease size is measured in square feet (Transaction SQFT). Statistics are calculated from the final estimation sample.

Table A.9: CompStak Data Coverage for Office Markets (Q3 2025)

Market	CompStak SQFT	Total Inventory	Vacancy Rate	Occupied Inventory	Coverage (%)
Washington	89,378,226	111,121,315	21.1%	87,674,718	101.94
San Francisco	59,390,124	86,371,302	27.1%	62,964,679	94.32
Manhattan	294,766,776	417,941,446	18.5%	340,622,278	86.54
Seattle	33,280,336	68,892,314	28.4%	49,326,897	67.47
Tampa	16,518,402	31,019,812	16.7%	25,839,503	63.93
Chicago	102,376,077	239,582,894	24.3%	181,364,251	56.45
Austin	27,437,123	67,603,287	23.3%	51,851,721	52.91
Charlotte	23,114,223	57,005,704	21.7%	44,635,466	51.78
San Diego	24,995,527	71,202,581	13.0%	61,946,245	40.35
Atlanta	41,926,165	157,897,916	23.2%	121,265,599	34.57
Boston	54,633,666	198,710,348	15.6%	167,711,534	32.58
Miami	10,851,561	39,524,844	14.9%	33,635,642	32.26
Denver	26,849,465	121,419,438	23.8%	92,521,612	29.02
Los Angeles	47,677,680	212,213,904	21.3%	167,012,342	28.55
Dallas	41,899,650	217,247,112	24.2%	164,673,311	25.44
San Antonio	10,193,511	50,356,651	16.0%	42,299,587	24.10
Phoenix	16,204,780	87,840,304	22.8%	67,812,715	23.90
Houston	33,056,202	183,659,815	23.6%	140,316,099	23.56
Arlington	22,095,414	130,295,271	23.1%	100,197,063	22.05
Philadelphia	25,071,907	139,567,264	17.3%	115,422,127	21.72
Irvine	14,863,403	89,492,438	17.4%	73,920,754	20.11
Portland	9,012,223	59,647,809	21.7%	46,704,234	19.30
Las Vegas	5,442,299	40,909,289	13.1%	35,550,172	15.31
Sacramento	8,759,742	69,322,903	14.5%	59,271,082	14.78
Oakland	7,350,863	95,286,844	17.7%	78,421,073	9.37
San Jose	12,358,507	226,103,465	12.2%	198,518,842	6.23

Note: This table shows CompStak's data coverage for Office markets as of Q3 2025. Coverage is calculated as the ratio of outstanding lease square footage in CompStak to occupied office inventory (total inventory × (1 - direct vacancy rate)) from Cushman & Wakefield. Occupied inventory excludes subleases.

Table A.10: Comparison of Distribution between Newly Added Leases and Existing Leases

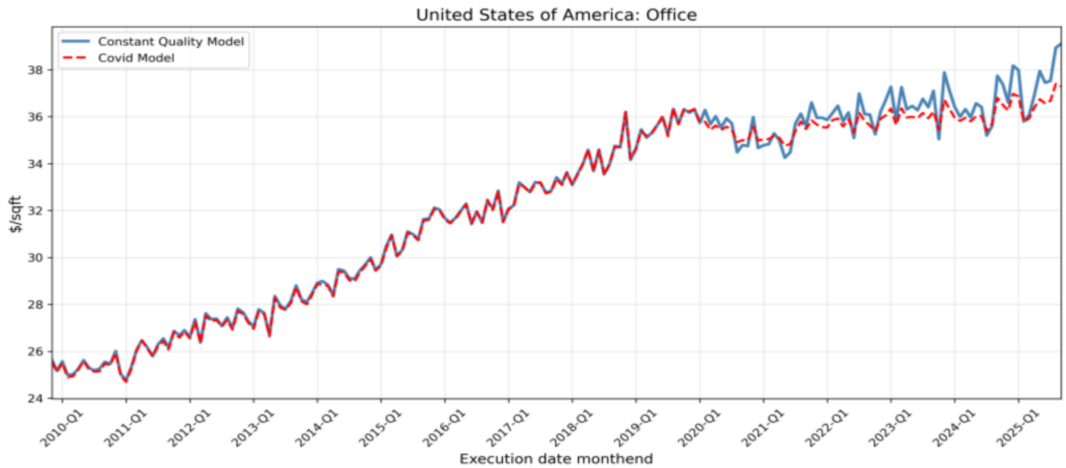
Characteristic	**Sample**	**Type**	**10%**	**25%**	**50%**	**75%**	**90%**
Lease Size (sqft)	National	New	900	1,500	3,157	10,276	35,897
	National	Existing	879	1,642	3,796	11,279	34,841
	Manhattan Office	New	2,278	4,733	8,229	16,504	40,051
	Manhattan Office	Existing	1,525	3,028	6,023	13,734	33,810
NER ($/sqft)	National	New	8.81	13.45	20.65	34.11	60.00
	National	Existing	6.96	12.00	19.38	29.77	46.26
	Manhattan Office	New	40.00	49.80	64.48	83.63	101.65
	Manhattan Office	Existing	33.00	41.67	52.62	66.72	84.29
Building Class A	National	New			36.5%		
	National	Existing			37.7%		
	Manhattan Office	New			56.5%		
	Manhattan Office	Existing			50.6%		
N	National	New			12,799		
	National	Existing			882,662		
	Manhattan Office	New			310		
	Manhattan Office	Existing			25,911		

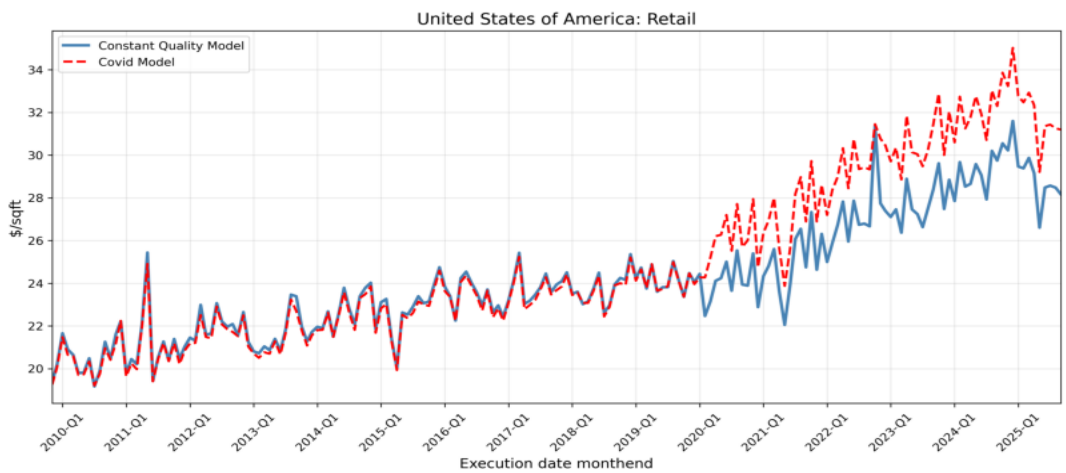
Note: This table compares percentile cutoff values for lease size and NER of new leases added in 2025-12-10 and existing leases (from 2025-10-10 dataset), and presents the percentage of leases with building class A for each case.

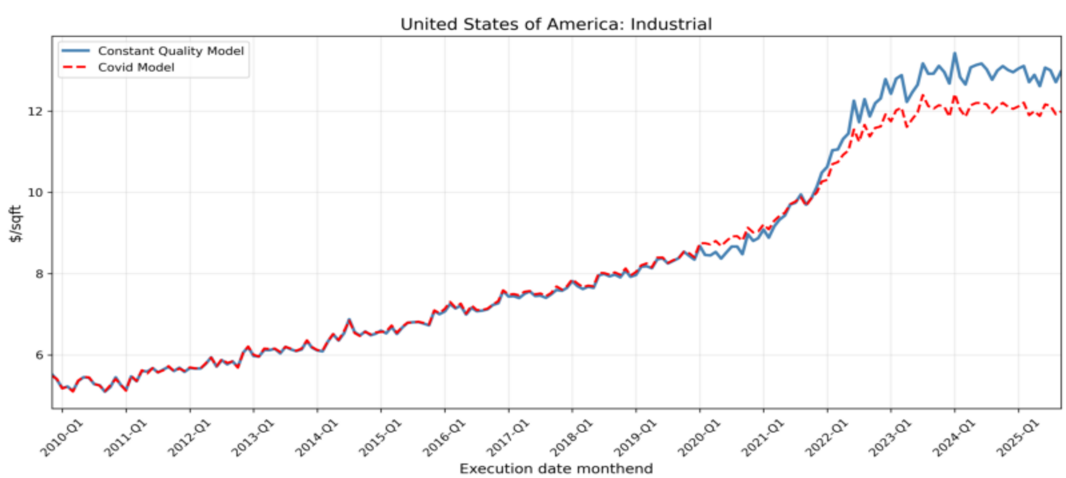
Table A.11: National Results (Pre vs Post COVID)

Coefficient	Office CQR	Retail CQR	Industrial CQR
Log Lease Size	-0.001 (0.001)	-0.221*** (0.004)	-0.065*** (0.002)
Log Building Size	0.006 (0.004)	-0.019*** (0.003)	-0.028*** (0.003)
Log Lease Term	0.045*** (0.002)	0.177*** (0.006)	0.064*** (0.003)
Log Renovation Age	-0.022*** (0.001)	-0.046*** (0.003)	-0.041*** (0.002)
Log Average Floor	0.031*** (0.002)	-0.067 (0.066)	0.531*** (0.092)
Clear Height Std	-	-	-0.016*** (0.003)
1_{CBD}	0.217*** (0.062)	0.031 (0.095)	0.103* (0.043)
1_{covid}*Log Lease Size	-0.004 (0.002)	-0.034*** (0.007)	-0.015*** (0.003)
1_{covid}*Log Building Size	0.000 (0.001)	0.001 (0.001)	0.005*** (0.001)
1_{covid}*Log Lease Term	-0.020*** (0.004)	0.000 (0.009)	0.027*** (0.005)
1_{covid}*Log Renovation Age	-0.015*** (0.002)	-0.010* (0.004)	0.023*** (0.003)
1_{covid}*Log Average Floor	0.000 (0.002)	-0.004 (0.018)	0.024** (0.008)
1_{covid}*1_{CBD}	-0.034*** (0.006)	-0.153*** (0.024)	-0.003 (0.022)
1_{covid}*Clear Height Std	-	-	0.039*** (0.004)
Missing Variable Flags	✓	✓	✓
Lease Type	✓	✓	✓
Transaction Type	✓	✓	✓
Tenant Industry	✓	✓	✓
Building Class	✓	✓	✓
Space Subtype	✓	✓	✓
Hierarchical FE	✓	✓	✓
Observations	489264	181444	219689
R^2	0.849	0.809	0.825

Figure A.1: National Net Effective Rents: Baseline vs. Covid Specification

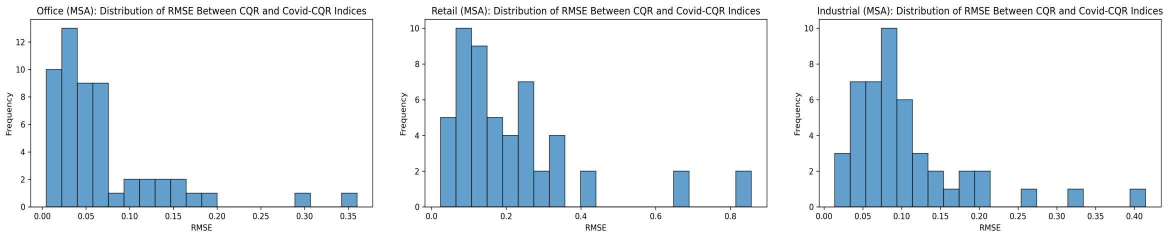






Notes: The post-Covid specification allows slope coefficients (β) to differ after March 2020. To ensure continuity, the first post-Covid point is spliced to align with the last pre-Covid value.

Figure A.2: RMSE Differences in CQR Indices: Benchmark vs. Covid-Specific Hedonics



Note. Histograms include only MSAs with at least 32 common quarterly observations between the CQR and Covid-CQR indices.

Figure A.3: Flexible Functional Form for Covariates: GAM vs. OLS

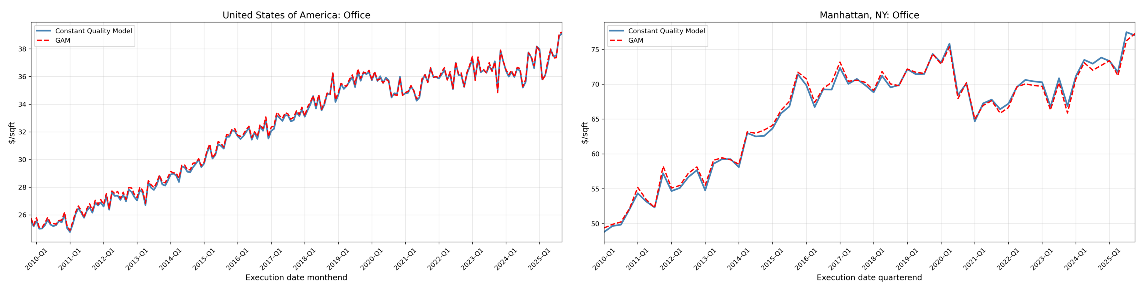


Figure A.4: Flexible Functional Form for Covariates: LGBM vs. OLS

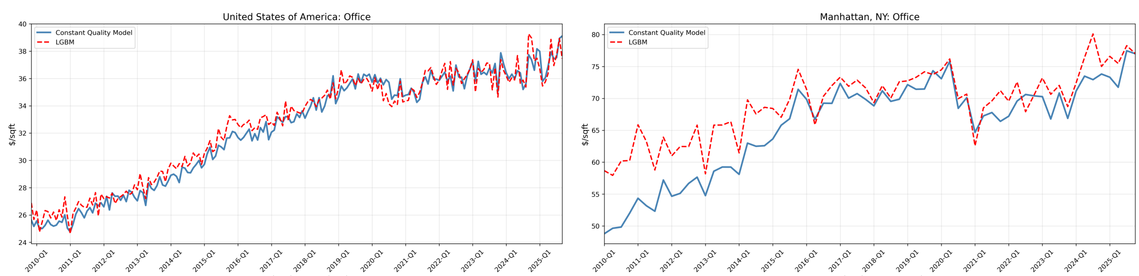
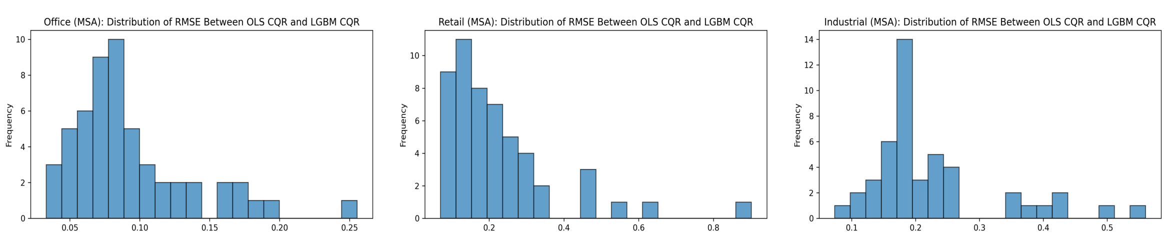


Figure A.5: RMSE Differences in CQR Indices: Benchmark OLS vs. LGBM



Note. Histograms include only MSAs with at least 32 common quarterly observations between the CQR and LGBM indices.