Received: Added at production | Revised: Added at production | Accepted: Added at production

DOI: xxx/xxxx

ORIGINAL ARTICLE

Crowded and Expensive: Density Shift as a Measure of Demand in Large US Apartment Markets

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Abstract

We introduce the Rental Density Index (RDI)—a novel, simple, scalable measure of rental housing demand based on grouping rather than spatial density—and demonstrate its predictive and diagnostic power across U.S. metropolitan markets. Using panel data from the 100 largest MSAs (2000-20024), we show that changes in RDI reliably signal future rent growth and provide a cap over which supply leads to declining rent. Using a two-stage least squares (2SLS) framework to address simultaneity between rents and density shifts, we establish the index as a robust measure of demand. To validate its real-world utility, we conduct a suite of tests: implementing event studies of regime transitions, benchmarking performance against other forecasting models, and examine RDI-supply imbalances during supply shocks. By capturing latent demand pressures even in fully occupied markets, RDI offers a scalable, transparent alternative to traditional metrics such as occupancy or absorption. Our results suggest that RDI can serve as both a predictive tool for rent growth and a benchmark for evaluating whether supply pipelines are aligned with underlying demand.

KEYWORDS
density, supply and demand, multifamily rent-growth, apartment markets

1 | INTRODUCTION

Housing shortages and affordability concerns have risen to the forefront of policy debates in major urban markets. In the United States, housing production has consistently lagged population growth for decades, contributing to an estimated national shortfall of 4.4 million housing units (Betancourt, 2022). Nearly half of U.S. renter households now spend over 30% of their income on housing (Bureau, 2022), and from 2000 to 2024, the consumer price index (CPI) for shelter exceeded the CPI for all other items by 30% (of St. Louis, 2024). At the same time, select high-growth regions have recently experienced rent declines due to a glut of new supply (Mott, 2024). This juxtaposition of chronic national undersupply with localized oversupply underscores a deeper issue: the lack of a reliable metric to measure consumer housing demand.

Traditional indicators of demand in multifamily real estate, such as occupancy rates and net absorption, are informative but fundamentally supply-constrained. Occupancy rates are naturally bounded at 100%, and absorption cannot exceed the rate of new deliveries (Mueller & Laposa, 1999). These constraints obscure excess demand: when all available and affordable units are occupied, latent demand becomes invisible to market participants and researchers alike (Gabriel & Nothaft, 2001; Sirmans, Sirmans, & Benjamin, 1991; Pyhrr, Cooper, & Wofford, 1999). This problem inhibits clear attribution of rent increases to supply versus demand dynamics (Pennington, 2021; Molloy, 2022). Moreover, ongoing academic debate persists around whether rising rents in constrained markets result more from supply-side limitations (Saiz, 2010) or from heightened demand for desirable locations (Davidoff, 2015). Without a transparent, consistent demand-side metric, attempts to assess equilibrium conditions remain incomplete.

In this paper, we introduce a novel empirical measure of rental housing demand: the *rental density index* (RDI), defined as the number of people per existing rental unit in a given metropolitan area. Unlike occupancy or absorption, RDI is not inherently bounded and therefore can reflect intensifying demand even in fully occupied markets. The conceptual foundation

Abbreviations: MSA, Metropolitan Statistical Area; RDI, relative density index;

is straightforward: as rents rise, renters economize on space—whether by delaying household formation, taking on roommates, or crowding—thus increasing the ratio of people per rental unit. By observing shifts in RDI over time, we capture underlying demand pressures that traditional metrics obscure.

Present trends support this reframing of demand, as density, rental prices, and rental preferences have all shifted meaningfully. For most of its history, the U.S. was less densely populated than its high-income peers, but in 1992 this changed. In that year, the US grew to 28 people per square kilometer, outpacing the High Income countries whose average was 23 people per square kilometer (Bank, 2025). The most recent figures report the US with a density of 36 and the High Income nations with an average density of 27. Over this same period, rental prices have outpaced both wages and non-shelter inflation (Feiveson et al., 2024; of St. Louis, 2024), with younger cohorts increasingly preferring rental housing (Mae, 2023).

Prior literature in urban economics and real estate has studied density extensively, often linking increased geographic density to higher wages, rents, and productivity due to agglomeration effects (Titman, Wang, & Yildirmaz, 2024; Liu, Pan, & Li, 2018). However, these studies generally define density in terms of spatial density: people per square mile or apartments per square mile. Our focus differs: we define density as the quotient of population over occupied rental units, which provides a clearer window into the number of people actively competing for housing. Unlike geographic density, this measure is directly responsive to shifts in demand, especially during periods of supply constraint or shocks.

Our framework builds on the standard assumption that, all else equal, households derive higher utility from larger living spaces (Muth, 1969; Molloy, 2022). In high-rent markets, however, the extra price per square foot may eventually exceed the marginal benefit of additional space. To economize, renters may respond by sharing units (adding roommates), downsizing to smaller apartments, or relocating to less expensive regions. Conversely, when real rents fall or new supply comes online, the marginal cost of extra space might drop below its marginal utility, enticing households to spread out, move to larger units, or reduce unitshare.The aggregate effect of these choices combined with the new supply additions or subtractions determines the direction the Rental Density Index change. Because the RDI directly captures these spaceconsumption margins, yearoveryear changes in RDI proxy for shifts in aggregate housing demand at prevailing prices.

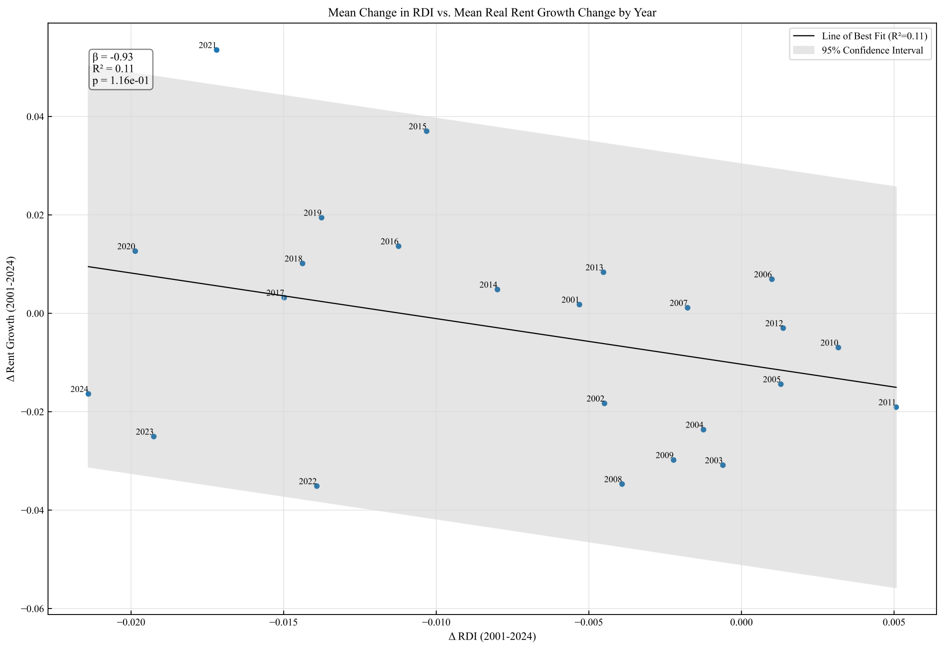


FIGURE 1 Relationship between average annual change in Rental Density Index (horizontal) and average annual relative real rent growth (vertical) in the 100 largest MSAs for each year between 2001 and 2024.

Focusing on a panel of the 100 largest metropolitan statistical areas (MSA) between 2000 and 2024, we calculate the RDI. We then examine the year-over-year change in each MSA, in each year. A positive change in RDI (densification) means that population has grown faster than inventory; conversely a negative change in RDI (de-densification) corresponds to inventory growing faster than population. While this ignores the number of households and the percentage of owners versus renters, the signal from the RDI change is robust in spite of this.

This empirical strategy reveals consistent rent growth differences across multiple time horizons. Over the one-year horizon, top RDI growth markets significantly outperform the bottom RDI growth quintile markets. The densifying markets outperform the de-densifying markets by over 100 basis points in real relative rent growth. The RDI growth also has very strong foresight with the trailing 10 year changes highly predictive of the next 10 years of supply growth and rent growth. The RDI is especially powerful when analyzed with observed supply growth. It serves as an indicator of when supply will be accretive to rent versus dillutive. In years and markets where the next year's supply exceeds the prior year's RDI growth, real rent growth is significantly below zero. Conversely, when supply is less than the RDI growth, the real rent is significantly greater than zero. These findings suggest that density-based classifications have predictive power and reflect latent demand more accurately than traditional indicators alone.

Our paper makes two principal contributions. First, we introduce the Rental Density Index (RDI), a novel, supply-unbounded metric of housing demand that can be computed at scale from readily available population and unitstock data. Second, we demonstrate RDIs empirical value using a suite of use-cases applicable to investors, renters, developers, and policy-makers.

These findings carry immediate applications for all housingmarket stakeholders. For policymakers, RDI functions as an early-warning gauge of emerging shortages, enabling targeted zoning reforms, calibrated subsidy programs, or expedited permitting in precisely those submarkets under the greatest pressureand subsequently measuring the efficacy of those measures. Institutional investors and residential developers can embed RDI trends into feasibility and risk models, avoiding the twin hazards of overbuilding in cooling metros or underbuilding in tightening ones. Finally, RDI sharpens the housingaffordability debate by identifying the locales where rent increases are most likely to outstrip income growth, thereby guiding tenantprotection policies, rentassistance programs, and other affordability interventions to the communities that need them most.

In the next section we discuss research on other measures of demand before presenting details on our proposed variable. The Data and Descriptive Statistics section describes and analyzes the density data we used, while the Empirical Analysis section presents evidence and illustrates statistical tests performed to evaluate the validity of the classifications. The final sections discuss the results of our tests before concluding with implications and further research suggestions.

2 | BACKGROUND AND LITERATURE REVIEW

The multifamily housing market has long relied on a narrow set of demand indicators, notably occupancy rates and net absorption. These indicators, while intuitively appealing and widely used by practitioners, are fundamentally constrained by the available stock of housing units. Occupancy rates cannot exceed 100%, and net absorption can never exceed new supply (Mueller & Laposa, 1999; Gabriel & Nothaft, 2001). Consequently, they fail to capture periods of latent demand where tenants cohabitate. (Sirmans et al., 1991; Pyhrr et al., 1999). Occupancy in particular has become an especially measure of demand since the advent of algorithmic pricing systems. So-called revenue management systems adjust rent pricing with the goal of keeping occupancy very near 96%, (CalderWang & Kim, 2024) the result of which is a variable with little signal.

This measurement limitation is consequential. Numerous empirical studies find that real rent growth often occurs in periods of high occupancy, yet they typically ascribe this to supply constraints rather than to excess demand (Goodman, 1992; Wheaton, 1991). While such studies validate the predictive value of these metrics, their theoretical bounds limit their explanatory reach, particularly when trying to assess equilibrium or derive true demand elasticities (Pennington, 2021; Molloy, 2022).

Alternative approaches to measuring demand have included econometric estimates of demand elasticity (Green, Malpezzi, & Mayo, 2002a), consumer preference surveys (Malpezzi & Green, 1996b), and utility-based choice models (Rosenthal, 1997a). However, these methods either lack the spatial and temporal granularity needed for policy or investment use, or they are not publicly available in standardized formats.

The broader urban economics literature has focused on density as a related but distinct construct. Seminal work by (Glaeser et al., 2001) and (Duranton & Puga, 2004) positions geographic density—typically measured as people or housing units per square mile—as a proxy for agglomeration benefits. These studies find that higher density correlates with increased productivity, innovation, and wages. However, they stop short of using density as a direct measure of housing demand.

More recent research has explored density in the context of housing affordability. (Ahlfeldt & Pietrostefani, 2019) and (Albouy et al., 2015) argue that densification can both alleviate and exacerbate affordability issues, depending on its implementation. For instance, densification may increase supply and reduce rents in the long term but may also create localized price pressures or quality-of-life tradeoffs that drive demand elsewhere.

Our work contributes to this literature by redefining density as *people per rental unit*, rather than per geographic area. We call this the Rental Density Index (RDI). This formulation allows demand to exceed supply in a measurable way: if population grows faster than units, density rises. If renters prefer space and are observed to cohabitate only at higher prices, then shifts in RDI reveal the slope of the underlying demand curve (Muth, 1969; Molloy, 2022).

Unlike geographic density, which may be influenced by zoning and land use policy, RDI responds directly to demographic pressures and consumer decisions. Its changes over time—ΔRDI—can be interpreted as demand shocks, analogous to shifts in labor force participation or consumption behavior in macroeconomic models. By linking ΔRDI to rent outcomes, we recover a market-clearing framework that identifies over- and under-supplied markets and projects likely rent growth trajectories.

Prior research has extensively modeled housing demand through price elasticity estimates (Green, Malpezzi, & Mayo, 2002b), utility-based choice models (Rosenthal, 1997b), and discrete consumer preference surveys (Malpezzi & Green, 1996a). These approaches contribute valuable structural insight into renter behavior, but they typically require extensive microdata on incomes, preferences, or migration patterns, and often assume equilibrium conditions. In contrast, our Rental Density Index (RDI) framework offers a simple, scalable alternative that avoids these data demands while directly capturing revealed behavior at the aggregate level. Rather than estimating the slope of the demand curve through price responsiveness alone, we observe actual changes in space consumptioncrowding or de-crowdingas rents rise or fall. This allows the RDI approach to reflect latent or excess demand even in fully occupied markets, where traditional elasticity estimates may fail to detect ongoing pressures. Our contribution is thus complementary to elasticity studies: whereas elasticity models estimate how much demand shifts in response to price changes under assumed conditions, RDI directly observes whether demand pressure exists at current prices by measuring household adjustments in space per person. In doing so, we provide a practical tool for market segmentation and forecasting that operates even when underlying micro-preference data are unavailable or incomplete.

This approach also aligns with emerging calls in the real estate literature to develop forward-looking, demand-side indicators that complement the traditional focus on supply elasticity (Glaeser & Gyourko, 2019). In contrast to existing studies, our method uses widely available data—population, rental unit inventory, and rent—to produce a scalable, repeatable measure of housing demand at the metro level.

In sum, our contribution lies in reinterpreting a well-studied spatial metric—density—through the lens of consumer housing decisions. By focusing on the population-to-unit ratio rather than geographic dispersion, we provide a new empirical tool to better understand and forecast real estate market dynamics.

3 | DATA AND DESCRIPTIVE STATISTICS

Our data are sourced primarily from Costar and supplemented with inflation measures from the U.S. Bureau of Labor Statistics. We restrict our analysis to the 100 largest U.S. metropolitan statistical areas (MSAs) by multifamily inventory as of 2001, ensuring robust sample representation and consistency over time.

To normalize pricing data across time, we convert all nominal rent figures into real terms using the Consumer Price Index for All Urban Consumers (CPI-U), all-items, provided by the BLS. Although MSA-level inflation indices excluding rent would be ideal, such data are unavailable at a consistent and granular level for our study period. Therefore, real effective rent per square foot and rent growth metrics are adjusted using national CPI.

We convert the rent growth figures to real as well, by subtracting the annual growth in CPI. Finally, we standardize the figures by subtracting the year's median rent growth. We do this to remove the impact of national macroeconomic shocks (i.e., COVID-19). This also serves to stationarize the data and remove the autoregressive tendencies of timeseries data.

Our novel demand variable, the Rental Density Index (RDI), is calculated by dividing population by total rental units at the MSA level. We compute its year-over-year percentage change—ΔRDI—to reflect demand dynamics more accurately. This measure avoids the bounded structure of traditional demand indicators like occupancy and absorption, which are upper bounded by 100%.

Other variables include supply growth, computed as the ratio of delivered units to the previous year's inventory, and lagged variables prior-year rent growth.

We exclude New Orleans, LA from our analysis because of its dynamics around the unfortunate aftermath of Hurricane Katrina. Within two years, this MSA had the greatest and least values of RDI growth as well as the greatest and least values of real rent change.

TABLE 1 Key variables used in the empirical analysis.

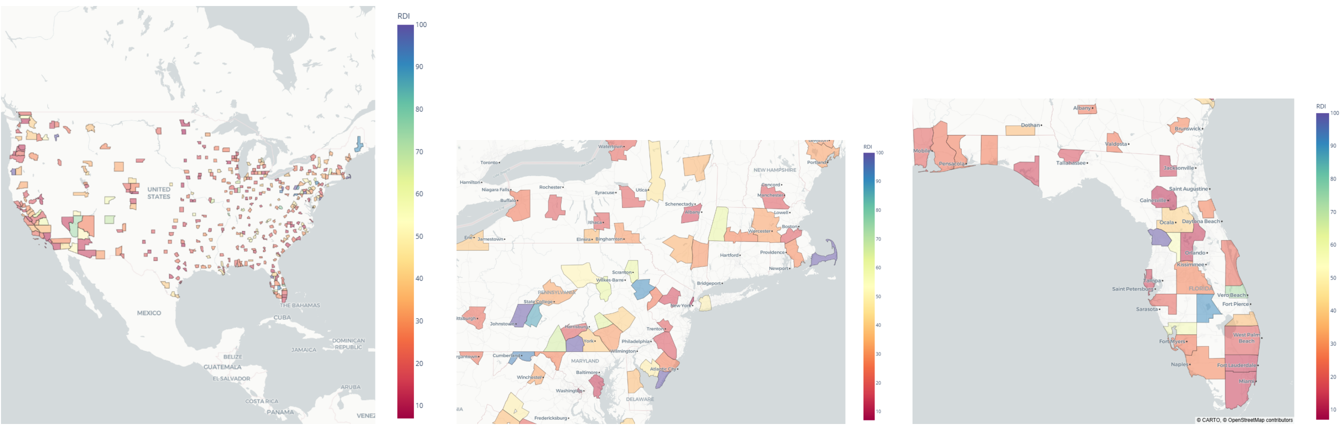
Variable	Description
`CPI`	Consumer Price Index for All Urban Consumers: All Items in U.S. City Average
`real_rentpsf`	Costar’s Rent Per Square Foot divided by indexed `CPI`
`real_rent_growth`	Costar’s Effective Rent Growth 12M less Annual percent change in `CPI`
`relative_real_rent_growth`	`real_rent_growth` less that year’s median `real_rent_growth`
`inventory`	Existing multifamily rental stock
`delivered`	Units delivered in the current year
`pop`	Total MSA population (Costar/Moodys)
`RDI`	Population divided by rental inventory
`delta_RDI`	Yearoveryear percentage change in `RDI`
`supply_growth`	Delivered units asă% of prior year’s `inventory`

3.1 | Variable Construction

The key outcome variable in this study is the *Rental Density Index* (RDI), calculated as the total population divided by the number of rental housing units in a given MSA-year:

$$\mathrm{RDI}_{it} = \frac{\mathrm{Population}_{it}}{\mathrm{Rental\ Units}_{it}}.$$

Within the 100 MSAs in the study,this metric ranges from 6.8 to 64.8. It reflects the number of people per rental unit.



(a) United States (b) Tri-State area (c) Florida

FIGURE 2 Rental-Density-Index (RDI) choropleths at three spatial scales.

While the RDI itself is useful for identifying how tight a market is at a given point in time, its absolute level is shaped by long-run demographic and structural trends such as rentership rates and changes in household formation. Accordingly, we focus on the *year-over-year change in RDI*:

$$\Delta\mathrm{RDI}_{it} = \mathrm{RDI}_{it} - \mathrm{RDI}_{it-1}.$$

The change in RDI (ΔRDI) offers several advantages. First, it mitigates issues of nonstationarity in the level RDI, enabling cross-market comparison. Second, it reduces the impact of varying rentership percentages across cities. Most importantly, ΔRDI captures demand pressure on housing stock: when it rises, it indicates more people are consolidating into fewer rental units, signaling tightening demand. When it falls, it implies renters are spreading out and absorbing more space, suggesting slack.

Theoretically, under the assumption that renters prefer more space to less, the change in RDI reveals when prices are sufficiently high to induce cohabitation and when price relief allows individuals to live separately. Thus, ΔRDI, especially when combined with rent growth, helps identify periods of excess demand or slack and allows us to trace out implied demand curves.

As we show later, this approach allows us to locate the intersection between demand and supply curves using observable outcomes.

3.2 | Summary Statistics

Table 2 provides descriptive statistics for the key variables across the full panel. On average, the RDI across all MSAs and years is approximately 2.31 persons per rental unit, with a standard deviation of 0.35. The average real rent per square foot is \$1.22, and the average annual growth in rental supply is 1.9%. The missing records exist only in the beginning or ending years as the prior period and next-period values do not exist.

TABLE 2 Summary Statistics (2000–2024)

Variable	Mean	Std. Dev.	Min	25thăPct.	Median	75thăPct.	Max	Missing
Population	2,012,976	2,169,231	175,653	758,060	1,224,731	2,422,333	14,849,020	0
Inventory	133,435	190,354	20,783	35,735	66,261	153,774	1,572,425	0
Supply growth	0.0169	0.0152	0.0173	0.0057	0.0059	0.0239	0.1061	100
RDI	18.259	6.852	6.841	13.737	17.067	20.967	64.795	0
RDI growth	0.0078	0.0151	0.1895	0.0163	0.0059	0.0022	0.0512	100
Real rent ($/sqft)	0.9489	0.3551	0.5584	0.7164	0.8373	1.0436	2.9110	0
Real rent growth	0.0035	0.0300	0.1915	0.0215	0.0046	0.0114	0.2809	100

3.3 | Coverage and Representativeness

The sample includes approximately 1,300 MSA-year observations, covering a mix of large coastal cities, fast-growing Sun Belt metros, and slower-growing Midwestern regions. Together, these MSAs account for over 16 million of the 22 million U.S. apartment units, providing a representative snapshot of national rental dynamics.

3.4 | Preliminary Observations

Figure 3 traces the national Rental Density Index (RDI) from 2000 to 2024. Contrary to conventional wisdom about an acute housing shortage, we observe a steady decline in people per unit (from roughly 16 people-per-unit in 2000 to 13 people-per-unit in 2024). A companion histogram of RDI is stationary but skewed slightly negative, confirming that most years see more units added per new person than vice versa.

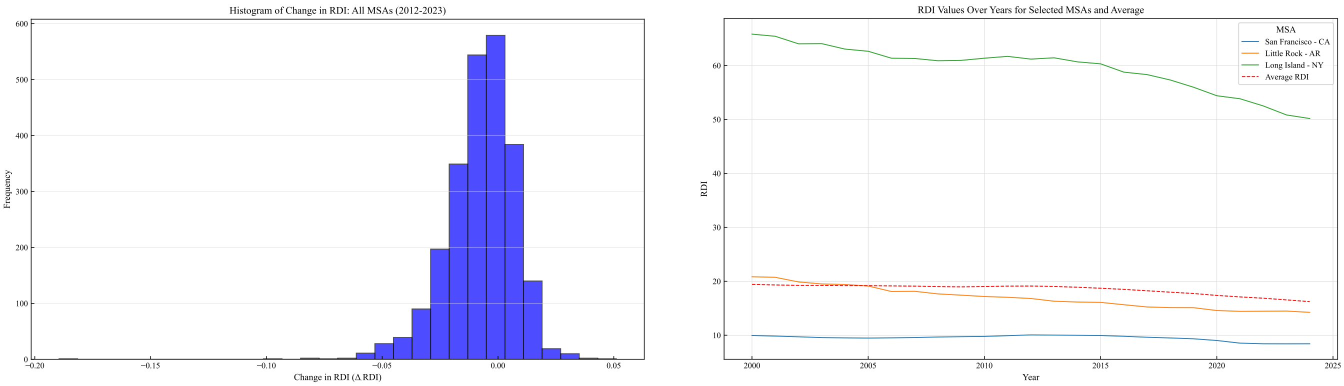
This pattern poses a puzzle: if supply growth has outstripped population growth, why is everyone still worried about shortages? Occupancy simply tells you *that* units are full–it cannot distinguish whether they are full by choice (everyone prefers roommates) or by necessity (everyone must share).

By contrast, year-over-year changes in RDI isolate the relative pace of new households versus new units. When rents rise faster than new construction can absorb, RDI spikes, revealing latent demand pressure. When deliveries overwhelm demand, RDI falls, signaling surplus. In the next section we exploit that property, regressing RDI on rent and supply growth to recover the underlying demand curve.

4 | EMPIRICAL STRATEGY AND ECONOMETRIC RESULTS

4.1 | Identification Strategy

We aim to estimate the causal effect of crowding—as measured by growth in the Rental Density Index (RDI)—on future rent growth. However, RDI may be endogenous to unobserved demand shocks, reverse causality, or simultaneity with rents. For



(a) A histogram of the annual change in RDI across 100 MSAs in the years 2001-2023. The outlier to the left is New Orleans in 2004, due to Huricane Katrina.

(b) A line graph showing the RDI values (population divided by apartment units) for the MSAs that were the min, max, and median in year 2001

FIGURE 3 Histogram of Change in RDI, and Line Graph of RDI

example, rising rents may force household compression, inflating RDI, or latent demand factors may affect both rents and occupancy intensity.

To address this, we use a two-stage least squares (2SLS) estimation strategy, instrumenting RDI growth with an exogenous migration shock. This shock is defined as a binary indicator equal to one when international in-migration exceeds the 90th percentile across all MSA-years from 2000 to 2024. This threshold identifies years of unusually high foreign population inflows plausibly unrelated to local rent conditions. We control for population growth and sales volume growth, and include MSA and year fixed effects.

$$\text{Stage 1:} \quad \Delta\text{RDI}_{i,t} = \gamma_0 + \gamma_1 \cdot \text{Shock}_{i,t} + \gamma_2 \cdot \mathbf{X}_{i,t} + \mu_i + \delta_t + u_{i,t}$$

$$\text{Stage 2:} \quad \text{RentGrowth}_{i,t+1} = \alpha_0 + \beta \cdot \widehat{\Delta\text{RDI}}_{i,t} + \alpha_1 \cdot \mathbf{X}_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t}$$

Where:

- RentGrowth$i, t+1$ is next-year relative real rent growth in MSA i,
- ΔRDIi, t is the change in Rental Density Index,
- Shocki, t is the migration shock instrument (defined as above),
- $\mathbf{X}i, t$ includes controls: population growth and sales volume growth,
- μ_i and δ_t are MSA and year fixed effects.

4.2 | Baseline Results

Table 3 shows that instrumented RDI growth significantly predicts future rent growth. A one-point increase in RDI growth is associated with a 1.29 percentage point increase in next-year rent growth.

4.3 | Robustness Tests

We conduct two robustness tests to validate our identification strategy.

1. Placebo Test. Using same-year rent growth as the dependent variable weakens the effect of RDI growth, suggesting RDI leads rent rather than the reverse.

2. Lagged Instrument. Replacing the contemporaneous migration shock with its lag ($\text{Shock}_{i,t-1}$) yields a similar point estimate with slightly lower precision.

TABLE 3 2SLS Estimates: RDI Growth and Next-Year Rent Growth

	Coefficient	Std. Error	t-stat	p-value
RDI\growth	1.2865	0.4171	3.085	0.0020
Population Growth	-0.0038	0.0019	-1.963	0.0496
Sales Volume Growth	4.1653	0.8401	4.958	0.0000
MSA Fixed Effects	Yes			
Year Fixed Effects	Yes			
First-stage F-stat	45.051			
Observations	1,863			

TABLE 4 Placebo Test: RDI Growth on Same-Year Rent Growth

	Coefficient	Std. Error	t-stat	p-value
RDI\growth	1.0994	0.4126	2.665	0.0077
Population Growth	-0.0011	0.0019	-0.573	0.567
Sales Volume Growth	5.5281	0.8555	6.462	0.0000
First-stage F-stat	76.214			
Observations	1,863			

TABLE 5 Lagged Instrument: RDI Growth and Next-Year Rent Growth

	Coefficient	Std. Error	t-stat	p-value
RDI\growth	1.2803	0.7152	1.790	0.0734
Population Growth	-0.0037	0.0033	-1.100	0.2711
Sales Volume Growth	4.5286	0.8548	5.298	0.0000
First-stage F-stat	40.087			
Observations	1,782			

4.4 | Interpretation and Limitations

Across all specifications, RDI growth remains a positive and statistically significant predictor of next-year rent growth. The placebo test demonstrates that the effect weakens for contemporaneous rents, supporting a forward-looking relationship. The lagged-instrument model confirms the robustness of this effect, though with expected attenuation.

These results support the interpretation that crowding—as measured by RDI—reflects latent demand pressure that translates into future rent growth. Our findings are consistent with a causal interpretation and are robust to multiple instrument timing and exclusion validity checks. Results are stable across alternative shock thresholds, including the 85th and 95th percentiles (see Appendix Table A1).

5 | FORECASTING VALIDATION AND REAL-WORLD PERFORMANCE

5.1 | Predictive Segment Testing: ANOVA on RDI Growth

We test whether observed changes in RDI can segment markets into meaningful groups in terms of future rent performance. Specifically, we split the samples into two regimes: those with positive ΔRDI and those negative ΔRDI. We then examine whether average next-year relative real rent growth differs significantly across these groups.

Table 6 shows that markets with positive RDI growth experience average next-year rent growth of 41 basis points above the mean rent growth (significant at p$\leq$ 3.14^{-14}), while markets with non-positive RDI growth exhibit an average decline of 15 basis points (significant at p$\leq$0.0026). The difference is statistically significant, as confirmed by both a one-way ANOVA and Tukeys HSD post-hoc test.

A two-way ANOVA confirms the significance of the group difference (F = 49.2, $p \leq 2.98 \times 10^{-12}$), and a Tukey HSD test further validates that the difference in means is statistically distinguishable.

TABLE 6 ANOVA of Next Year's Relative Real Rent Growth Grouped by RDI

ΔRDI Group	Mean (bps)	SE (bps)	95% CI Lower	95% CI Upper	n	p-value
RDI Decline	-15	5	-25	-5	1538	0.0026
RDI Growth	41	7	31	52	762	3.14^{-14}

TABLE 7 Two-Way ANOVA Test Results

Term	Sum Sq	DF	F	p-value
C(demand)	0.0165	1.0	49.23	2.98^{-12}
Residual	0.7699	2298.0	—	—

TABLE 8 Tukey HSD Test Results

Group 1	Group 2	Mean Diff	p-adj	Lower	Upper	Reject
Δ RDI $\leq$0	ΔRDI>0	0.0057	0.0000	0.0041	0.0073	True

These results show that even without instrumentation, RDI growth serves as a powerful signal for forward rent performance. Practitioners can use RDI segmentation as a lightweight, interpretable classification rule for identifying tight rental markets.

5.2 | Event Study of RDI Regime Transitions

We next evaluate how rent growth responds dynamically to transitions into and out of RDI-growth regimes. Specifically, we examine rent growth before and after a market switches into a state of positive ΔRDI (increasing crowding) or negative ΔRDI (declining crowding). We continue to examine results in terms of real rent growth relative to the mean rent growth of that year, to avoid capturing rent changes due to macro conditions.

Figure 4 illustrates rent growth over a five-year window centered on the regime switch. The blue line represents transitions into crowding markets, the red line transitions into de-densifying markets, and the gray line shows cases where RDI status does not change.

Table 9 reports differences in average rent growth before and after the regime shift. Markets transitioning into crowded segments see a 48 basis point increase in rent growth, while those exiting see a 29 basis point decline. No significant change is observed when RDI status remains unchanged, as expected.

TABLE 9 Mean Rent Growth Before and After RDI Regime Transition

Transition Type	Mean Before	Mean After	Difference	p-value
Switched to ΔRDI > 0	-31	17	48	0.0027
Switched to ΔRDI $\leq$ 0	52	23	-29	0.0089
No change	-3	-8	-5	0.6336

These dynamics confirm that the onset of crowding pressures, as measured by RDI, precedes statistically and economically meaningful changes in rent performance. RDI transitions can therefore serve as timely indicators of shifts in market pricing power.

5.3 | Forecast Spread Comparison: RDI vs ARIMA vs Naïve

We compare the predictive strength of RDI growth against ARIMA-based and naive trailing average models in forecasting real rent growth across multiple time horizons. For each method, we rank MSAs into quintiles based on their predicted growth

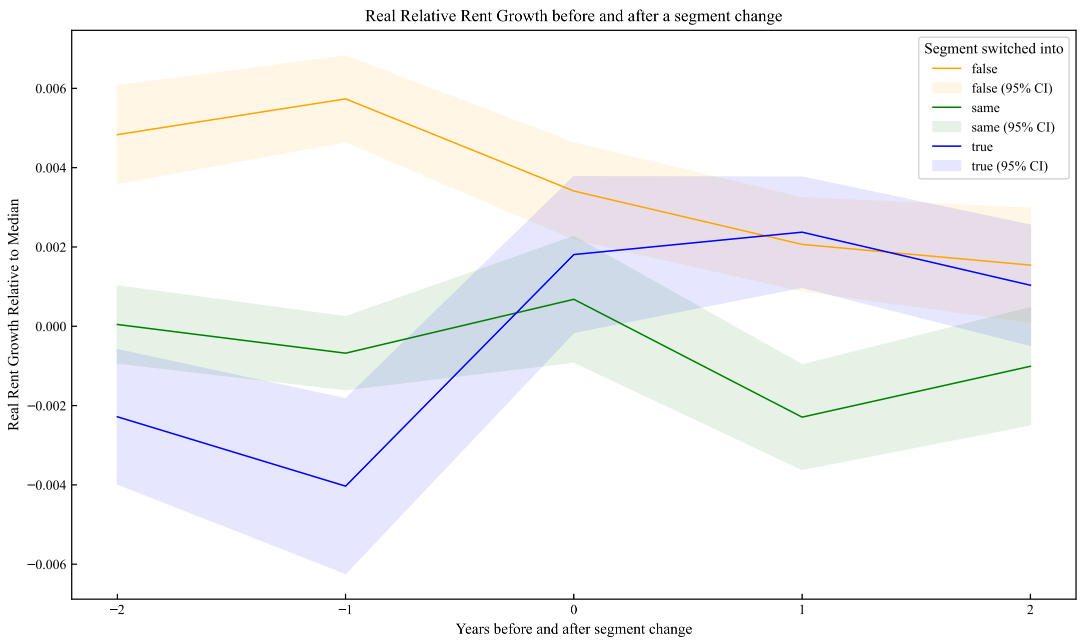
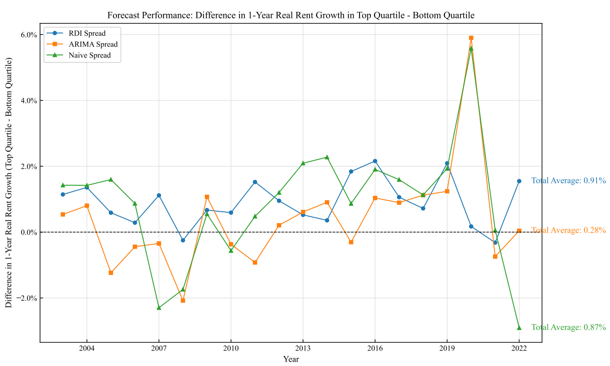
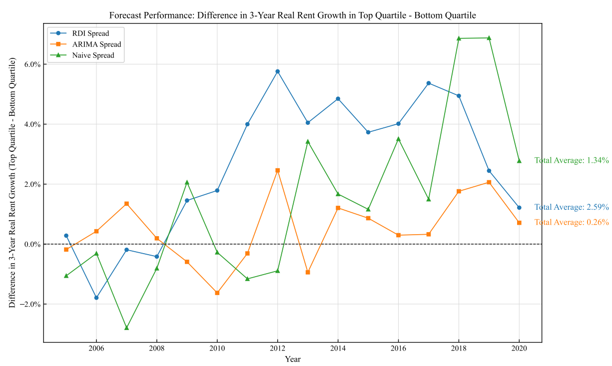


FIGURE 4 Real Relative Rent Growth Before and After a Market Switches From/To Positive/Negative ΔRDI

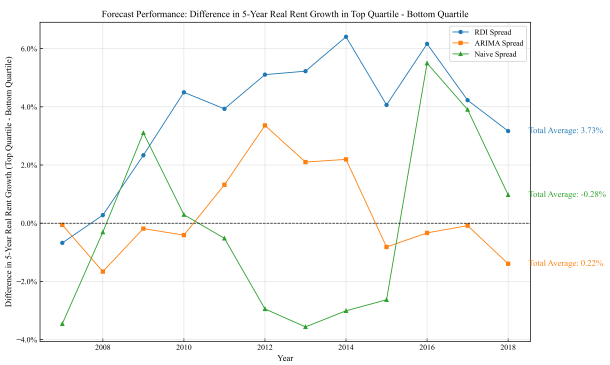
and compute the realized top-minus-bottom quintile spread. Figure 5 displays forecast accuracy over one-year, three-year, five-year, and ten-year windows. The RDI-based approach consistently delivers stronger spread segmentation, particularly at longer horizons where traditional time-series methods tend to degrade.



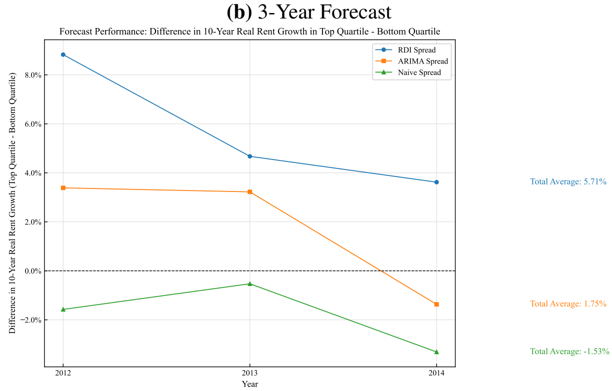
(a) 1-Year Forecast



(b) 3-Year Forecast



(c) 5-Year Forecast



(d) 10-Year Forecast

FIGURE 5 Top-minus-Bottom Quintile Rent Growth Spread by Forecast Method and Horizon

These results reinforce the value of RDI as not only a causal explanatory variable but also a forward-looking predictive signal. Forecasting long-term rent growth is notoriously difficult; most models lose power beyond a few years. The fact that the RDI-based approach maintains signal strength across one-, three-, five-, and ten-year periods underscores its robustness. While time series models rely on trailing trends, RDI captures forward-looking, structural occupancy pressuremaking it an effective long-horizon indicator of underlying demand.

5.4 | Distributional Evolution and Market Cycles

Here we take a meta-examination of the classification system. The groupings are not evenly distributed across years, as we did not enforce an artificial standardization. Instead, this reflects underlying market behavior rather than methodological bias.

TABLE 10 Market Classification and Average Real Rent Growth (2011–2024)

Year	Neutral-Early	Renter-Friendly	Landlord-Friendly	Neutral-Late	Avg. Real Rent Growth
2011	61%	0%	36%	3%	-2%
2012	36%	2%	60%	2%	0%
2013	26%	2%	67%	5%	1%
2014	22%	1%	64%	13%	1%
2015	9%	7%	38%	46%	4%
2016	4%	8%	26%	62%	1%
2017	3%	7%	22%	68%	0%
2018	2%	6%	17%	75%	1%
2019	2%	6%	7%	85%	2%
2020	1%	5%	6%	88%	1%
2021	0%	8%	3%	89%	6%
2022	2%	8%	13%	77%	-4%
2023	5%	3%	21%	71%	-3%
2024	2%	8%	30%	60%	-1%

In early years such as 2011, few MSAs exhibit characteristics of overpriced and oversupplied markets, consistent with post-crisis housing conservatism. By contrast, between 2020 and 2022, the vast majority of MSAs fall into the Neutral-Late category, despite negative or flat rent growth. This asymmetry suggests the framework captures real cyclical shifts, where high observed rents and heavy supply growth outpace renter willingness or ability to absorb space. The sharp contrast between high pricing and poor performance in these years further reinforces the frameworks value in signaling impending cooling phases or market corrections.

5.5 | Predictive Power and Caveats

To gauge if the predictive power offered by the model is significant, we compare it to the forecasts of an ARIMA model and a naive model. The ARIMA model looks at trailing-10 year periods and forecasts the next year. The naive model assumes that the markets that were the top performers in the prior year will continue to be top performers in the following year. We then take the average rent growth of the forecasted top third and subtract it from the average rent growth of the forecasted bottom third.

The relative-density system had a spread of 172 basis points between its Landlord-Favorable and Renter-Favorable markets, when grouped by year. The ARIMA model had a spread of 145 basis points, while the naive model had a spread of 153 basis points. This suggests the implied demand signal can be used to rank markets by expected future performance, offering both interpretability and predictive power.

A potential concern with our approach is that rents and supply choices may themselves be influenced by unobservable expectations about future demand, introducing endogeneity between price, supply growth, and the change in rental density (RDI). To mitigate this, our identification strategy relies on rolling 10-year historical windows to estimate demand and supply relationships, using only lagged data to derive equilibrium benchmarks for each market-year. This structure limits direct contamination from forward-looking decisions into the classification framework. Nonetheless, we acknowledge that residual simultaneity could bias estimates if, for example, developers respond to unmeasured leading indicators not captured in our

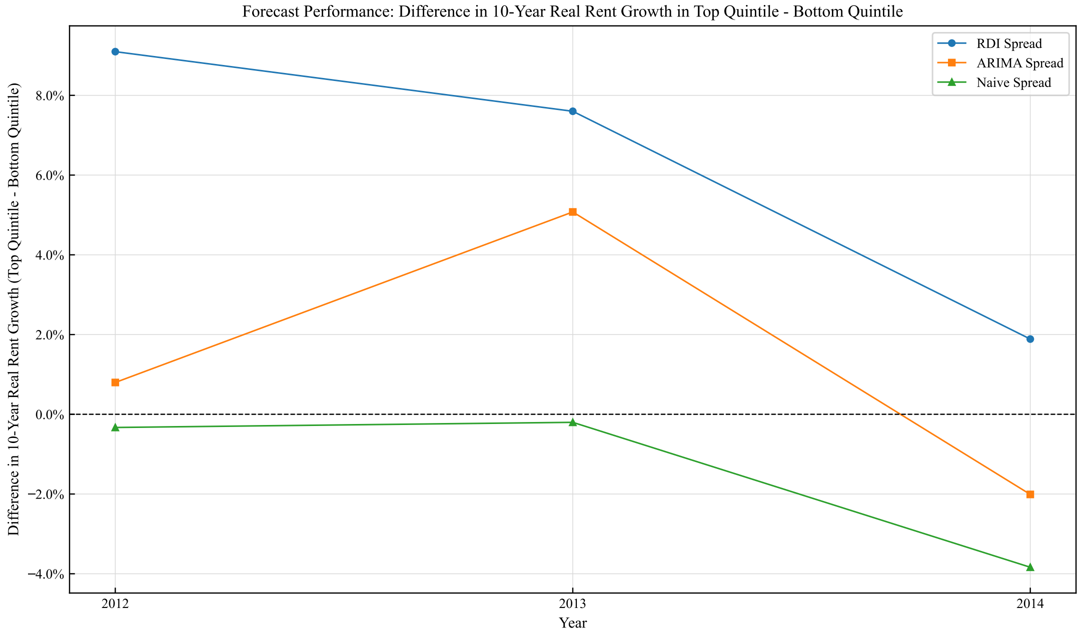


FIGURE 5 Event study of average real rent growth before and after entry into the Overpriced & Oversupplied regime ($t = 0$).

regressions. While fully addressing this would require valid external instrumentssuch as exogenous supply shocks driven by zoning changes or permitting delays (e.g., (Saiz, 2010))data limitations prevent their inclusion in this analysis. As a robustness check, we incorporate lagged dependent variable models and fixed effects at both the market and year level to absorb time-invariant and macroeconomic confounders. The consistency of our results across these specifications provides some reassurance that endogeneity does not fully drive the observed relationships. We highlight this as an area for future research and encourage replication using instrumented designs where feasible.

Together, these findings validate the informational value of market misalignment relative to derived equilibrium, offering a parsimonious and predictive classification of multifamily rent dynamics.

TABLE 11 Yearly Spread Comparison

Year	RDI Spread	ARIMA Spread	Naive Spread
2012	0.0123	0.0023	0.0141
2013	0.0246	0.0056	0.0141
2014	0.0446	0.0113	0.0183
2015	0.0264	0.0176	0.0239
2016	0.0195	0.0230	0.0139
2017	0.0124	0.0123	0.0201
2018	0.0080	0.0181	0.0110
2019	0.0136	0.0087	0.0122
2020	0.0284	0.0119	0.0265
2021	-0.0005	0.0110	0.0113
2022	0.0118	0.0530	-0.0073
2023	0.0058	-0.0006	0.0251

6 DISCUSSION

Our findings reinforce the utility of rental density—measured as population per occupied rental unit—as a robust proxy for demand in multifamily housing markets. Traditional demand-side variables such as occupancy and absorption are bounded

TABLE 12 Average Spread Comparison

Variable	Average Value
RDI Spread	0.0172
ARIMA Spread	0.0145
Naive Spread	0.0153

above by 100%, rendering them structurally incapable of expressing excess demand. By contrast, our proposed measure, the change in Rental Density Index (ΔRDI), accommodates marginal and nonlinear shifts in tenant behavior, particularly around unit sharing or household formation.

The empirical evidence supports this theoretical proposition. When supply and demand curves were derived from historical ΔRDI and supply growth data, we observed that the relative position of actual market conditions to the implied equilibrium—quantified as overpriced/underpriced and oversupplied/undersupplied—was significantly associated with next-year rent growth. Specifically, markets that were both overpriced and undersupplied experienced statistically higher rent growth than other combinations. Conversely, renter-favorable markets (underpriced and oversupplied) exhibited lower growth or even declines.

This segmentation has both explanatory and predictive power. Our simplified ANOVA model revealed statistically significant differences in next-year rent growth across these market states. We presented an event-study model showing the impact of being classified as 'Renter-Friendly' and 'Landlord-Friendly' in the years following the classification. Finally we compared the predictive power of our classification system to that of ARIMA models and naive models used to forecast market rent-growth. In this comparison as well, our model outperformed.

While the number of MSAs in each state was not evenly distributed across years, this asymmetry reflects genuine market dynamics rather than bias or misclassification. For example, in periods of expansion, we naturally observe more overpriced or undersupplied markets, consistent with cyclical pressures on housing. Nonetheless, even in years with few markets in a given segment, those groupings consistently displayed expected behavior in rent trajectories.

These findings reinforce the value of ΔRDI as a continuous, forward-looking measure of housing demand, especially when contrasted with backward-looking or constrained alternatives. They also suggest that equilibrium misalignment—in both price and quantity—can be quantified in a way that is both actionable for investors and meaningful for policymakers.

7 | CONCLUSION

This paper contributes to the literature on housing market dynamics by introducing the change in Rental Density Index (ΔRDI) as a scalable, interpretable measure of demand. Unlike occupancy or absorption, ΔRDI captures variation in consumer preference through household formation behavior—a critical but often overlooked channel of adjustment in rental markets.

By modeling supply and demand curves separately and estimating their intersection, we were able to derive implied market-clearing quantities and prices for each metropolitan area in our dataset. These derived values allowed for the segmentation of MSAs into four quadrants based on price and supply misalignment. Across the 100 largest U.S. markets from 2010 to 2023, these quadrants were statistically associated with next-year rent growth in ways consistent with theory: undersupplied and overpriced markets performed best; oversupplied and underpriced markets performed worst.

This demand proxy also showed moderate predictive power when used in a linear forecasting framework, suggesting that it may serve as a leading indicator of rent pressure—particularly when combined with supply metrics. The ability to anticipate future rent dynamics is valuable to developers, institutional landlords, and policymakers seeking to manage affordability and stability in rental housing.

Future work should explore refinement of ΔRDI to account for compositional changes in renter populations and household structures. Additional improvements might include the integration of MSA-specific CPI indices or disaggregated demand inputs, such as migration, income distributions, or age cohorts. Nonetheless, the present analysis establishes ΔRDI as a conceptually valid and empirically useful measure of multifamily housing demand, with applications in forecasting, pricing, and supply planning.

AUTHOR CONTRIBUTIONS
All authors contributed equally

ACKNOWLEDGMENTS
FINANCIAL DISCLOSURE
CONFLICT OF INTEREST
DATA DISCLOSURE

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