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

DOI: xxx/xxxx

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.

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

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 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 Nations 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 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 of the Rental Density Index change. Because the RDI directly captures these space–consumption margins, year–over–year changes in RDI are proxies for shifts in aggregate housing demand at prevailing prices.

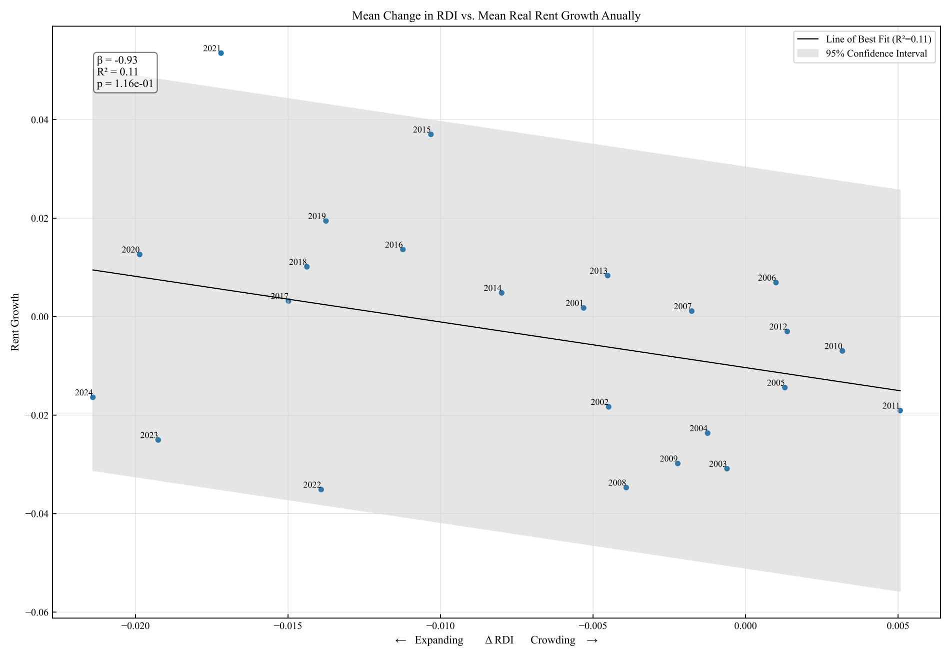


FIGURE 1 Relationship between average annual change in Rental Density Index (horizontal) and average annual relative real rent growth (vertical) in the 100 largest MSAs for each year between 2001 and 2024.

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, likely because ownership rates are fairly stationary relative to RDI.

This empirical strategy corresponds with consistent rent growth differences across multiple time horizons. Over the one-year horizon, positive RDI growth markets significantly outperform negative RDI growth markets. The densifying markets outperform the de-densifying markets by over 100 basis points in real 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 three 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 show the RDI is a significant indicator of latent demand, using a two-stage least squares model and a very broad panel of foreign in-migration data to measure demand shocks. Finally, 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 housing—market 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 pressure. 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 tenant–protection policies, rent–assistance 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 Strategy section presents evidence and illustrates statistical tests performed to evaluate the validity of the econometric model. In the Forecasting and Validation section, we evaluate the RDI in five different scenarios, showing its power in rent-growth forecasting. The final sections discuss the results of our tests before concluding with implications and further research suggestions.

2 | BACKGROUND AND LITERATURE REVIEW

A substantial literature in urban and housing economics has sought to measure rental demand using structural modeling, hedonic estimation, and affordability thresholds. Price elasticity estimates, often based on income and housing cost shares, provide insight into how demand responds to price movements under equilibrium assumptions (Green, Malpezzi, & Mayo, 2002a; Malpezzi & Green, 1996b). Hedonic models explain rent levels as a function of unit characteristics and neighborhood amenities, while housing affordability metrics attempt to measure stress via cost-to-income ratios. Though valuable, these approaches often require microdata that are unavailable across time and space or assume frictionless adjustment, limiting their utility in settings with short-run disequilibrium or constrained inventory.

The multifamily housing sector has traditionally relied on indicators such as occupancy rates and net absorption to characterize demand. These measures are intuitive and operationally convenient but are constrained by the size of the existing rental stock. Occupancy, by definition, cannot exceed 100 percent, and absorption is mechanically bounded by the number of new units delivered (Mueller & Laposa, 1999; Gabriel & Nothaft, 2001). As a result, such metrics are poorly equipped to detect latent demand, specifically periods in which prospective renters are unable to form households or must cohabitate due to limited supply or rising costs (Sirmans et al., 1991; Pyhrr et al., 1999). This limitation has become more acute in recent years as algorithmic revenue management systems increasingly target stabilized occupancy thresholds (for example, 95 to 96 percent), further muting variation and diminishing their informational content (CalderWang & Kim, 2024).

While these indicators retain short-run forecasting value, they offer limited theoretical insight into renter behavior under constraint. Several studies have documented rent growth during periods of high occupancy but tend to attribute this to restricted supply rather than suppressed household formation (Goodman, 1992; Wheaton, 1991). Structural models, including utility-based choice models (Rosenthal, 1997a) or equilibrium migration frameworks, provide more detailed behavioral inference but require data on preferences, incomes, or location-specific amenities that are rarely standardized across markets.

Parallel literature in urban economics has studied density, typically defined as people or dwellings per square mile, as a proxy for agglomeration or spatial efficiency. Seminal work by (Glaeser et al., 2001) and (Duranton & Puga, 2004) links higher density to economic productivity, while more recent studies explore the dual role of densification in shaping housing affordability and urban form (Ahlfeldt & Pietrostefani, 2019; Albouy et al., 2015). Yet geographic density is primarily a land-use metric; it does not directly reflect household formation or space consumption behavior.

Our work reframes density through a behavioral lens by defining it as the number of people per occupied rental unit: the Rental Density Index (RDI). This metric captures demand pressure more directly than geographic density by tracking how renters adjust their living arrangements under price or supply stress. If renters prefer more space but are observed to cohabitate as rents rise or supply tightens, an increase in RDI reflects a behavioral response to constrained conditions. Conversely, declines in RDI suggest slack: households can afford to spread out. Unlike traditional metrics, RDI growth (ΔRDI) enables analysts to detect crowding pressures even in fully occupied markets.

RDIs strength lies in its scalability and interpretability. Constructed from widely available data — population, and rental inventory — it offers a transparent, repeatable measure of latent demand across markets and over time. This approach is especially valuable in contexts where elasticity models fail to identify pressure due to equilibrium assumptions or unavailable microdata. While elasticity studies estimate how much demand shifts in response to price, RDI captures whether pressure exists at current prices through observed space consumption.

In sum, our contribution is to reinterpret a familiar spatial concept as a dynamic, renter-centered metric that reflects real-time demand conditions. By linking changes in RDI to rent performance, we introduce a new tool for housing market analysis that complements traditional models and offers practical value for forecasting, segmentation, and policy design.

3 | DATA AND DESCRIPTIVE STATISTICS

Our market data is sourced from Costar. This includes nominal rent per square foot and rental units by market. Our inflation measures come from the U.S. Bureau of Labor Statistics. And our foreign immigration data at the market level comes from the US Census. 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. We convert nominal rent-growth figures into real rent-growth figures by subtracting the annual CPI-U change from the annual rent per square foot change. 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.

Importantly, we standardize rent-growth subtracting each 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 quotient 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.

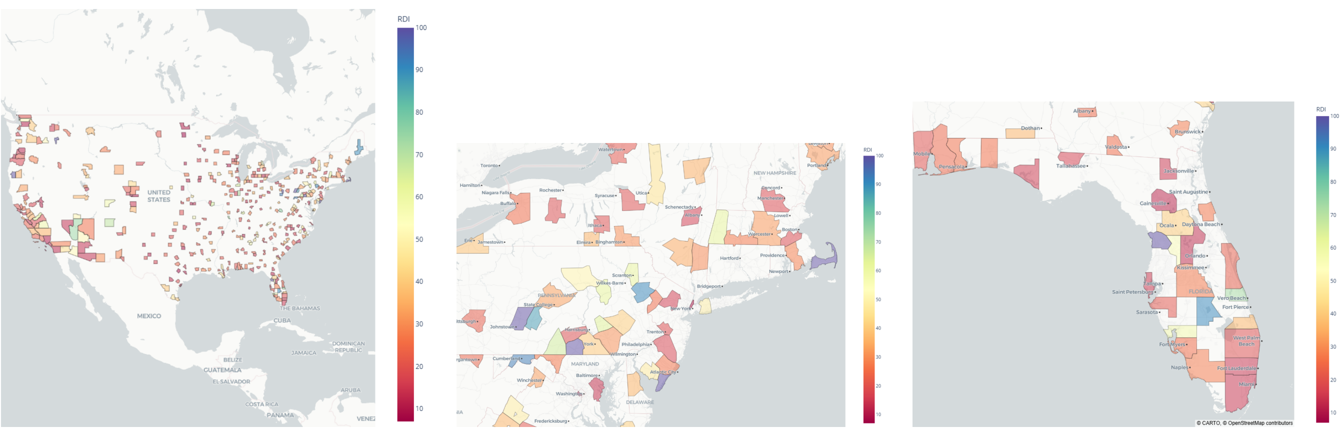
Variable	Description
`CPI`	Consumer Price Index for All Urban Consumers: All Items in U.S. City Average
`real_rentpsf`	Costar's Rent Per Square Foot divided by indexed `CPI`
`real_rent_growth`	Costar's Effective Rent Growth 12M less Annual percent change in `CPI`
`relative_real_rent_growth`	`real_rent_growth`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

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. It is useful to distinguish between two sources of crowding pressure captured by ΔRDI: price-induced and supply-induced. Price-induced crowding occurs when rising rents outpace incomes, forcing renters to share space or delay household formation—behavioral responses that directly elevate RDI. Supply-induced crowding, by contrast, may arise even without rent escalation if housing stock fails to expand alongside population, resulting in more residents per unit out of sheer constraint. While these mechanisms are observationally similar, our framework implicitly captures both, interpreting ΔRDI as the revealed outcome of frictions between housing availability and household spatial preferences. In this way, RDI growth reflects excess demand pressures regardless of whether they arise from affordability shocks or constrained supply.

It is important to note that ΔRDI is conditioned on the rental population and does not explicitly capture shifts between renting and homeownership. Data on home-ownership at the MSA level is sparse, beginning in 2005 and only for the 75 largest MSAs. Furthermore the margins of error are prohibitively large; they are regularly in excess of the annual change percentages and as high as 12.7% for a single quarter's measurement. Those limitations notwithstanding, the average annual change in homeownership in the largest 75 MSAs from 2015-2024 was 0.20%, suggesting stationarity. Still, in markets where tenure transitions are volatile—such as during periods of mortgage credit expansion or policy-driven ownership incentives—changes in RDI may partly reflect movement between tenures rather than intra-renter space consumption. For example, a declining RDI could reflect renters exiting into homeownership rather than an easing of rental crowding. While the vast majority of variation in ΔRDI likely reflects household formation and consolidation behavior within the rental market, readers should interpret RDI-based signals with awareness of broader tenure context, especially in markets with known ownership volatility. That said, the average annual change in home ownership is orders of magnitude smaller than either of the RDI components. Between 2002 and 2024 the average annual change in home ownership rate was -0.001, while the average annual change in rental units is 1.35% and the average annual change in population is 0.75% over the same time.

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 18 persons per rental unit, with a standard deviation of 7. The average real rent per square foot is $0.97, and the average annual growth in rental supply is 1.69%. 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

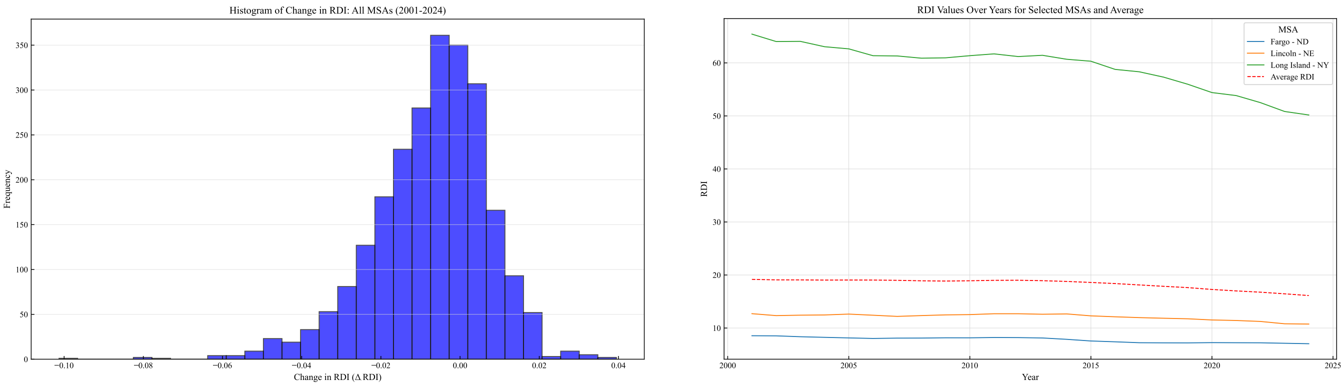
Unnamed: 0	count	mean	std	min	25%	50%	75%	max
pop	2500	2,010,409	2,176,842	175,485	752,856	1,213,619	2,422,780	14,897,850
inventory	2500	133,025	190,307	20,399	35,323	65,463	153,901	1,580,435
supply_growth	2400	0.02	0.02	-0.02	0.01	0.01	0.02	0.12
RDI	2500	18.37	7.04	7.04	13.78	17.09	20.89	65.82
RDI_growth	2400	-0.01	0.01	-0.1	-0.02	-0.01	0.0	0.04
real_rentpsf	2500	0.97	0.36	0.57	0.73	0.85	1.06	2.93
real_rent_growth	2400	-0.0	0.03	-0.14	-0.02	-0.0	0.01	0.2

3.3 | Coverage and Representativeness

The sample includes 2,500 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.



(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

This pattern illustrates the need for a different demand metric, otherwise the concern for housing shortage seems to be contradicted by a monotonically decreasing housing density. Said differently, occupancy simply reports 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 people versus new units. In the next section we investigate that property to reveal RDI as a proxy for latent demand.

4 | EMPIRICAL STRATEGY AND ECONOMETRIC RESULTS

We estimate the causal effect of crowding, measured as the change in the Rental Density Index (ΔRDI), on future rent growth using a two-stage least squares (2SLS) instrumental variables (IV) approach. This is necessary because ΔRDI may be endogenous to unobserved demand shocks or simultaneous determination with rents. For example, rising rents may compress household formation (raising RDI), or latent shocks could affect both rents and occupancy intensity.

To isolate exogenous variation, we instrument ΔRDI with foreign in-migration as a share of local population, capturing rare and plausibly unanticipated inflows. We implement two instrument definitions: continuous and binary. In the continuous specification, exog_shock_{it} is defined as the year's foreign in-migration as a percent of population. In the binary specification, $\text{exog\_shock}_{it} = 1$ when foreign in-migration exceeds 0.8% of population and 0 otherwise. This encompasses approximately 7.2% of MSA-years and corresponds to a natural break in the distribution of foreign migration.

To support the validity of these instruments, we confirm that lagged rent growth does not predict foreign in-migration shares. A fixed-effects panel regression of foreign migration share on lagged rent growth yields no significant relationship ($\beta = -0.415$, $p = 0.215$, detailed in Appendix A Section 7). This result supports the assumption that foreign migration shocks are exogenous with respect to prior local rental market conditions.

The empirical models are specified as follows:

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

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

Where:

- $\text{RentGrowth}_{i,t+1}$ is next-year relative real rent growth in MSA i,
- $\Delta\text{RDI}_{i,t}$ is the change in Rental Density Index (crowding pressure),
- $\text{Shock}_{i,t}$ is the instrumenteither foreign migration share (continuous) or high-migration indicator (binary),
- $\mathbf{X}_{i,t}$ includes controls: population growth and sales volume growth,
- μ_i and δ_t are MSA and year fixed effects.

Both specifications (continuous and binary) yield statistically significant and robust estimates. Using the continuous instrument, the estimated effect of ΔRDI is 2.31 (p = 0.0010), with a strong first-stage F-statistic of 30.3. A placebo test, which replaces the outcome with contemporaneous rent growth, returns a smaller and weaker coefficient (1.66, p = 0.0019), consistent with a forward-looking interpretation.

Using the binary instrument, the estimated coefficient is 1.68 (p = 0.0173), with an F-statistic of 39.9. The placebo result remains significant but slightly attenuated (1.61, p = 0.0183). While the binary version benefits from a cleaner exclusion argument, the continuous specification provides stronger statistical power and supports robustness across specifications.

In contrast, results from lagged instruments are weaker; neither continuous nor binary lagged instruments produce statistically significant estimates, suggesting a contemporaneous relationship between migration shocks and crowding pressure.

TABLE 3 Summary of 2SLS Estimates of ΔRDI on Next-Year Relative Rent Growth for both a Continuous and Binary Shock Variable

Instrument Type	Coef. on ΔRDI	Std. Err.	p-value	F-stat (1st Stage)
Continuous (contemp.)	2.31	0.70	0.0010	30.3
Continuous (placebo)	1.66	0.53	0.0019	62.4
Binary (contemp.)	1.68	0.71	0.0173	39.9
Binary (placebo)	1.61	0.68	0.0183	62.9
Lagged (continuous)	1.54	0.86	0.0740	42.8
Lagged (binary)	-0.35	1.02	0.7282	62.8

Together, these models confirm that exogenous migration shocks produce measurable increases in crowding pressure, and that these crowding effects reliably forecast future rent growth. All specifications include MSA and year fixed effects, ensuring that the estimated relationships are not confounded by time-invariant local characteristics or national-level shocks. The consistency of findings across instrument definitions and robustness checks strengthens confidence in ΔRDI as a causal and timely proxy for rental housing demand.

While the IV model provides a causal estimate of the effect of crowding pressure on rent growth, the subsequent tests in Section 5 evaluate whether ΔRDI can serve as a useful predictive signal. These forecasting models do not claim to identify structural relationships, but rather assess the practical value of RDI for anticipating future market conditions.

5 | FORECASTING VALIDATION AND REAL-WORLD PERFORMANCE

This section evaluates whether RDI functions as a useful predictive signal for rent growth, independent of causal identification. We organize the analysis into five complementary tests: (1) a simple group-wise ANOVA showing forward rent segmentation by RDI direction; (2) an event study evaluating rent dynamics before and after regime shifts in RDI; (3) a top-vs-bottom quintile spread comparison across forecasting models; (4) a long-horizon signal using count-based RDI persistence; and (5) a diagnostic of supply growth in context, showing how RDI mediates the impact of new supply. Together, these tests examine the predictive performance, durability, and explanatory clarity of RDI across diverse empirical contexts.

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 4 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 4 ANOVA of Next Year's Relative Real Rent Growth Grouped by RDI

ΔRDI Group	Mean Relative Rent Growth (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 5 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 6 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 7 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 7 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

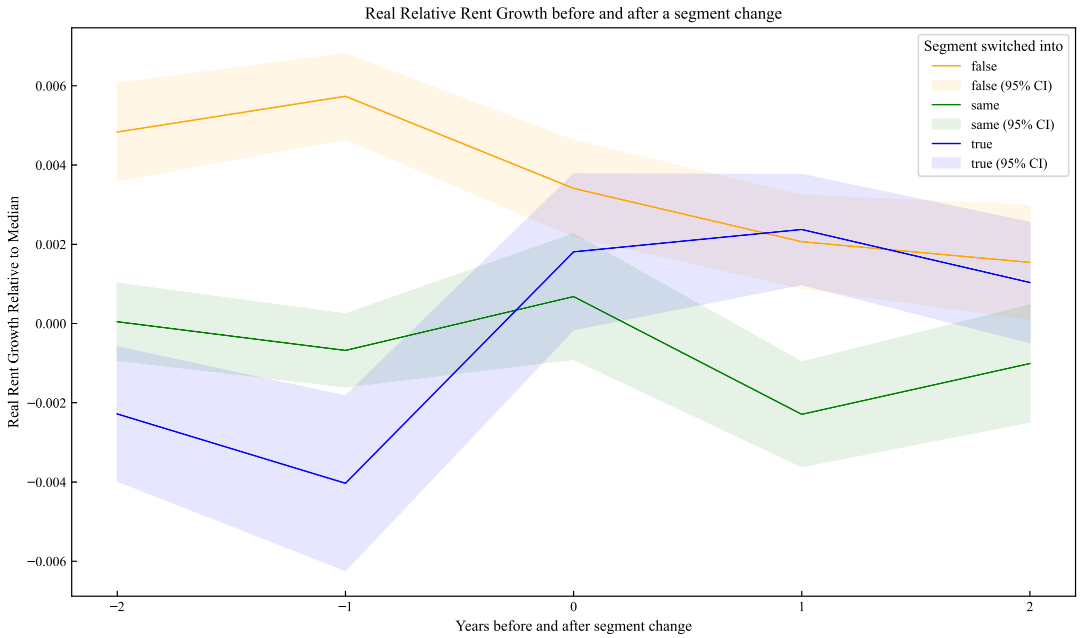
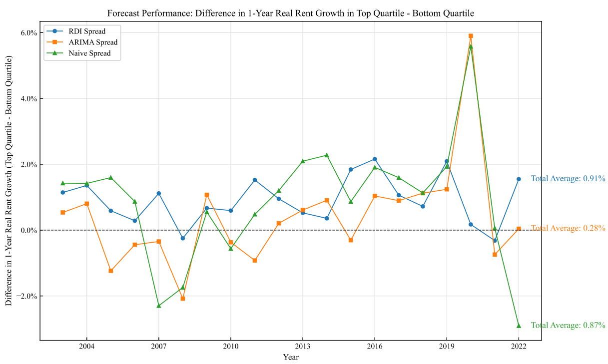


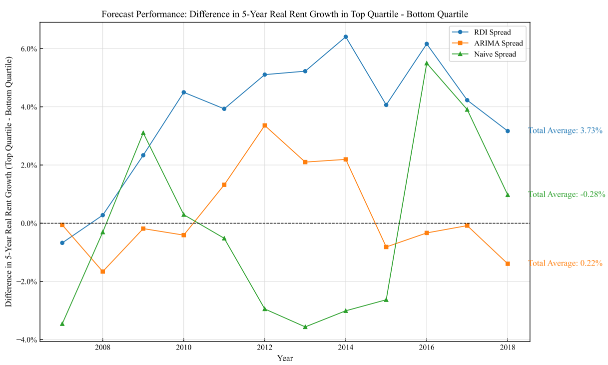
FIGURE 4 Real Relative Rent Growth Before and After a Market Switches From/To Positive/Negative ΔRDI

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.

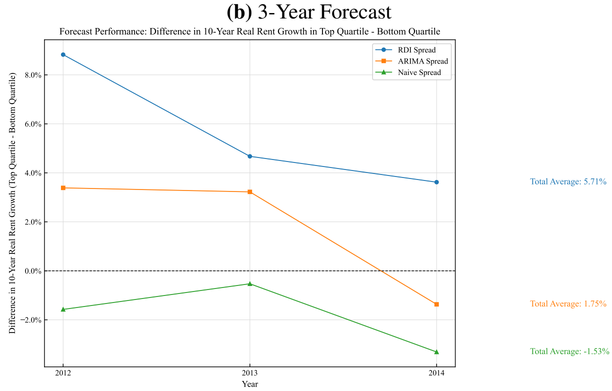


(a) 1-Year Forecast

(b) 3-Year Forecast



(c) 5-Year Forecast



(d) 10-Year Forecast

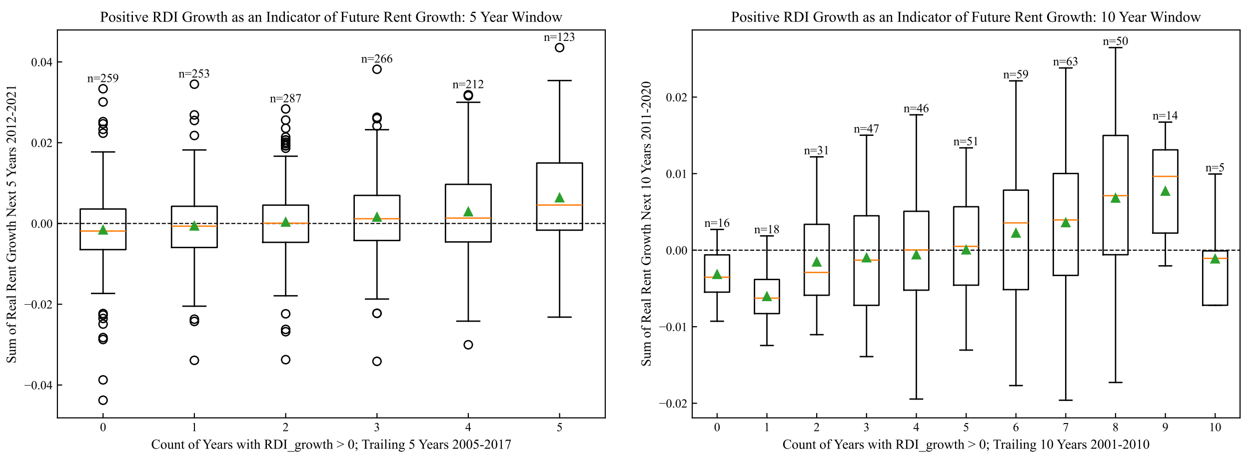
FIGURE 5 Top-minus-Bottom Quintile Rent Growth Spread by Forecast Method and Horizon

These results reinforce the value of RDI as a forward-looking predictive signal. Forecasting long-term rent growth is notoriously difficult; most models lose power beyond a few years. 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 | RDI Positivity Persistence and Long-Term Rent Growth

We test whether a simple count of trailing years with positive RDI growth serves as a meaningful predictor of future rent appreciation. Specifically, we show the cumulative rent-growth in the following x-years after observing counts of positive RDI growth in the trailing x-years. We look at this over 5 and 10-year rolling periods.

Figure 6 shows that when n is significantly large, there is a clear, monotonic relationship: markets with more positive RDI observations tend to experience stronger future rent growth. This pattern holds across both time horizons and supports the argument that RDI functions as a persistent, structural signal of housing demand.



(a) 5-Year Horizon **(b)** 10-Year Horizon

FIGURE 6 Cumulative Rent Growth by Number of Positive RDI Years in Prior Window

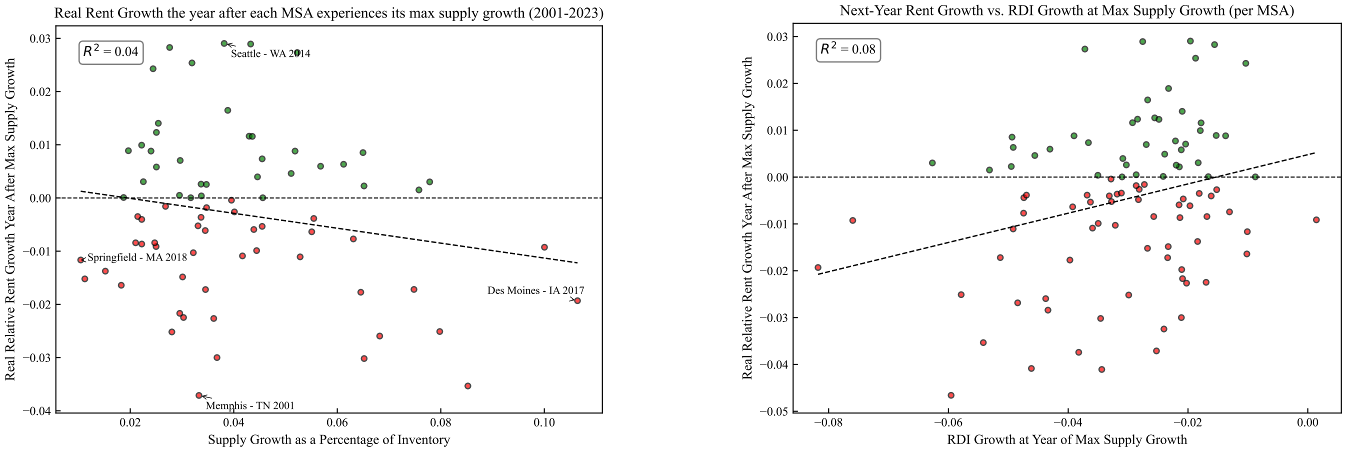
These results reinforce the practical utility of RDI: even without complex forecasting models, the simple count of positive RDI signals—interpreted as consistent crowding pressure—can help classify markets by likely long-term pricing strength.

5.5 | Supply Growth in Context: RDI as a Mediating Lens

It is often assumed that elevated supply growth should depress rents in subsequent years. To test this assumption, we identify each MSA's year of maximum supply growth and examine the subsequent years real relative rent growth. Figure 7a shows that the relationship is weak: nearly 45% of markets still experienced positive rent growth even after their peak supply year, and the overall correlation is low.

In contrast, when we examine how Δ RDI in those same years (Figure 7b), the relationship between supply growth rent growth is clearer. In markets where supply outstripped population growth the most (farthest left on the X-axis) the rent growth was lowest. Conversely, when supply growth—though at an all-time high— was closer to population growth, the rents responded more positively. This suggests that crowding pressures, not raw supply levels, capture more of the variance in subsequent rent performance. Even in high-supply environments, strong demand (captured by RDI) can offset what might otherwise appear to be oversupply conditions.

These results challenge the assumption that supply growth alone determines rent dynamics. Without considering how supply is absorbed relative to household formation, analysts risk misclassifying healthy markets as oversupplied. RDI offers a more reliable, demand-sensitive lens.



(a) Supply Growth vs. Subsequent Rent Growth

(b) Supply Growth vs. RDI Growth

FIGURE 7 Crowding Absorption During Maximum Supply Years

5.6 | Summary: RDI as a Practically Useful, Predictively Durable Demand Metric

The empirical tests in this section demonstrate that RDI—a simple, observable measure of household crowding—delivers meaningful insight into rental market behavior. Across multiple frameworks, RDI consistently outperforms: it segments markets with forward—looking rent divergence, anticipates regime transitions, and reveals demand absorption dynamics even during peak supply years.

These results complement the causal identification strategy in Section 4, where instrumented RDI growth was shown to drive future rent increases. Here, we show that RDI also performs well in practice without instrumentation, making it suitable for real-time forecasting, benchmarking, and investment decisions.

While RDI is not without limits—its precision may weaken in data-sparse MSAs or highly regulated rent environments—it stands out as a behaviorally grounded, interpretable, and statistically durable signal of latent housing demand.

6 | DISCUSSION

This paper demonstrates that crowding pressure, as measured by changes in the Rental Density Index, serves as a robust and forward-looking indicator of rental market tightness. Our empirical analyses show that ΔRDI reliably predicts future rent growth, highlighting the hidden intensity of rental housing demand even when traditional market metrics such as occupancy rates remain stable. By distinguishing between the causal role of ΔRDI in driving rent growth and its practical forecasting utility, we establish the broad applicability and effectiveness of this indicator. The findings underscore the versatility of ΔRDI as both a rigorous economic indicator of underlying market dynamics and a practical forecasting tool for diverse market participants.

6.1 | Advantages

Unlike traditional, static metrics such as occupancy and absorption, ΔRDI dynamically captures behavioral adjustments by households responding to housing constraints, such as increased roommate formation or delayed household formation. These early behavioral signals often precede rent increases, positioning ΔRDI as a valuable leading indicator.

Significantly, ΔRDI retains predictive strength across various forecasting horizons, consistently outperforming traditional ARIMA and naive trailing-average models, even in out-of-sample tests. Its predictive accuracy, particularly notable in forecasting rent trends over longer periods (such as ten-year horizons), underscores its robustness and practical applicability.

The clear implications for policy-makers, investors, and renters make ΔRDI particularly valuable. For policymakers, it offers an early warning signal of emerging housing shortages or surpluses, facilitating timely and targeted interventions such as zoning reforms, targeted subsidies, and expedited permitting processes. Investors and developers can integrate ΔRDI into their risk management and feasibility analyses, enhancing strategic decisions about market entry, asset allocation, and development timing. Renters benefit from clearer market signals about impending rent increases, enabling better-informed housing decisions and advocacy efforts. Thus, ΔRDI provides a structurally sound, scalable, and practical framework for anticipating and managing market dynamics across multiple contexts.

6.2 | Limitations: Tenure Shifts and Spatial Spillovers

While ΔRDI offers a parsimonious and scalable indicator of rental demand pressure, it is important to acknowledge two interpretive limitations. First, the framework assumes a stable tenure compositioni.e., that observed changes in population per occupied rental unit reflect shifts within the renter segment. However, in some markets, changes in RDI may be partially driven by tenure transitions, such as households moving into homeownership or into rental units from ownership due to credit constraints or housing cost burdens. For example, a declining RDI might suggest easing crowding pressure, but could also reflect renter outmigration into the owner-occupied segment. Conversely, increasing RDI may reflect ownership lock-in effects or affordability barriers that delay household formation. While these effects likely operate at the margin in most MSAs, acknowledging tenure fluidity is important for fully interpreting RDI-based signals. Future work could extend the RDI framework by incorporating tenure transition data or endogenizing homeownership trends.

Second, the current analysis treats each metropolitan statistical area (MSA) as an independent unit. In practice, however, housing market conditions are rarely contained by administrative boundaries. Migration, affordability spillovers, and commuting patterns often link neighboring MSAs, meaning that crowding pressures in one region may affect rental markets in adjacent areas. Ignoring these spillover dynamics may understate the correlated nature of demand shifts, especially in highly integrated urban corridors. Incorporating spatial dependence structures or spatially lagged RDI variables in future work may enhance model precision and improve detection of regional displacement or diffusion effects.

While we do not formally estimate a spatial lag model, we assess geographic clustering by examining pairwise correlations in ΔRDI across neighboring MSAs. We find strong co-movement among regionally linked marketse.g., New York and Northern New Jersey ($r = 0.70$), San Francisco and San Jose ($r = 0.69$), and DallasFort Worth and Austin ($r = 0.77$). More details can be found in Appendix B. These results suggest that crowding pressures often evolve in tandem across proximate metros, reflecting regional migration flows, shared housing constraints, or price spillovers. Future work could formalize these relationships using spatial dependence structures or migration-network adjacency matrices.

7 | CONCLUSION

We propose the Rental Density Index (RDI) as a demand-centric metric for measuring latent pressure in multifamily rental markets. By tracking changes in population per occupied unit, RDI captures household-level crowding dynamics that precede and predict future rent movement. Our empirical results, validated across causal models, forecasting tests, and event studies, establish (ΔRDI) as both a leading indicator and a practical classification tool.

The simplicity of RDI is a strength. While traditional demand estimation often requires detailed demographic or income data, RDI can be computed with widely available population and housing stock data. Yet it performs comparablyif not betterthan more complex models, especially over long forecast horizons. It is also behaviorally grounded: renters adjust space usage when pricing becomes constrained, and this adjustment leaves measurable traces in the data.

Future research may extend this work in several directions. RDI could be evaluated alongside migration flows, income segmentation, or micro-level leasing data to refine its predictive specificity. It may also prove useful in pricing models, rent control policy evaluation, or early-warning systems for affordability crises.

In sum, this paper offers both a new way to quantify housing demand and a practical framework for translating that signal into market insight. (ΔRDI) helps bridge the gap between structural economics and applied decision-makingand in doing so, offers analysts, policymakers, and investors a grounded, interpretable, and scalable tool for anticipating market behavior.

APPENDIX A: INSTRUMENT VALIDITY

To assess the exogeneity of our instrument, we test whether lagged relative rent growth predicts the share of foreign in-migration. We estimate:

$$\text{foreign\_migration\_share}_{i,t} = \alpha + \beta \cdot \text{RentGrowth}_{i,t-1} + \gamma \cdot \mathbf{X}_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t}$$

where $\mathbf{X}_{i,t}$ includes population growth and sales volume growth, and μ_i and δ_t represent MSA and year fixed effects. The coefficient on lagged rent growth is statistically insignificant ($\beta = -0.415$, $p = 0.215$), providing support for the orthogonality of foreign migration shocks to prior local rent conditions.

APPENDIX B: SPILLOVER EFFECT CORRELATION MATRIX

TABLE 8 Cross-MSA Correlation in ΔRDI Among Regional Pairs

MSA 1	MSA 2	Correlation (r)
New York, NY	Northern New Jersey, NJ	0.70
San Francisco, CA	San Jose, CA	0.69
DallasFort Worth, TX	Austin, TX	0.77
Los Angeles, CA	Inland Empire, CA	0.52
Miami, FL	Palm Beach, FL	0.54

AUTHOR CONTRIBUTIONS
All authors contributed equally

ACKNOWLEDGMENTS
FINANCIAL DISCLOSURE
CONFLICT OF INTEREST
DATA DISCLOSURE

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