Bargaining Outcomes of Housing Investors Across Diverse Communities**

Jeffrey Cohen[†, ¶], Roland Füss[‡, §], Chinmoy Ghosh[¶], and Darren Hayunga[$]

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Abstract: Recent research highlights investors' bargaining advantages in U.S. single-family housing markets. This study builds on prior work by examining how neighborhood characteristics—specifically income, race, age, education, and eviction trends—shape the market conditions under which investor negotiations occur. Our findings reaffirm investors' bargaining power while demonstrating how these outcomes vary across communities, particularly with respect to racial composition. Additionally, we illustrate how socioeconomic and socio-demographic factors, alongside eviction patterns, influence the types of properties investors acquire. To advance research on investors' net bargaining and demand effects, we introduce a novel empirical framework for future study.

Keywords: *Racial Discrimination; Bargaining Effects*; *Housing Markets*; *Real Estate Investors; Sociodemographic and Socioeconomic Characteristics*.

JEL-Classification: *C78, D12, D53, D83, E30, R21, R30, R31*

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[†] Community Development Group, Federal Reserve Bank of St. Louis
[¶] School of Business, University of Connecticut
[‡] Swiss Institute of Banking and Finance, University of St.Gallen
[§] NTNU Business School, Trondheim, Norway
[$] Terry College of Business, University of Georgia

1. Introduction

This paper examines how the socioeconomic and sociodemographic composition of intra-city communities, along with district-wide changes in eviction levels, influence price outcomes between investors and owner-occupiers in the U.S. single-family housing market. Specifically, we analyze the bargaining outcomes of these two groups, contributing to the growing body of research on residential real estate investment. This literature primarily falls into two streams: one investigating the bargaining advantages and disadvantages of different market participants and the other examining the expanding role of institutional investors, particularly in the aftermath of the Great Recession of 2007–09. Both areas of research are critical, as they highlight price disparities between owner-occupiers—who engage in relatively infrequent housing transactions—and more active market participants, including individual and professional investors, real estate agents, institutional investors, government agencies, and iBuyers.

Our analysis is motivated by two key considerations. First, while prior studies on investor bargaining outcomes account for localized effects, they typically rely on fixed effects at the census tract or subdivision level (Turnbull and van der Vlist, 2022; Cohen and Harding, 2023; Hayunga and Munneke, 2024). Although this approach captures spatial variation, it overlooks the role of sociodemographic and socioeconomic characteristics in shaping bargaining outcomes. We address this gap by explicitly incorporating these community-level attributes into our analysis, interacting them with investor bargaining power and demand functions. Using data from more than 2,400 census tracts in Los Angeles County, we provide a more nuanced understanding of how investor behavior varies across different market environments.

Rather than suggesting that investors bargain with communities, our framework recognizes that neighborhood characteristics shape the broader market conditions in which transactions take place. These tract-level characteristics can be central to intra-city variation in investor behavior and price dynamics. For example, the racial composition of a tract may reflect historical segregation patterns, credit access disparities, homeownership rates, and long-term wealth differentials. Age composition reflects tenure stability and market turnover, as older neighborhoods tend to have more established homeowners, while younger ones are often renter-dominated. Median income serves as a direct indicator of local economic status and purchasing power. It also tends to exhibit greater variability than race, age, or education in response to short-term economic fluctuations and is a strong predictor of housing affordability, market demand, and investor appeal.

Our second motivation stems from the lack of attention to tenant evictions in housing investment research, despite their potential to be a fundamental driver of investor price outcomes. In addition to a series of papers in the last decade on evictions, including Desmond (2012), Desmond and Kimbro (2015), Desmond et al. (2015), Desmond (2016), there are two important recent papers on the effect of evictions on the consequences of eviction for tenants (Collinson et al, (2024) and the relative demand of housing (Coulson et al. 2025). Separate from these studies, we examine how changes in eviction levels are associated with investor behavior and pricing outcomes, as eviction trends may signal neighborhood stability, rental market conditions, investment opportunities, housing supply dynamics, and risk perceptions—each of which can shape investor bargaining power. For instance, high eviction rates may indicate economic distress, instability, or declining property conditions, deterring owner-occupants who prioritize long-term stability and community investment. By contrast, investors may view such conditions as opportunities to acquire properties at discounted prices. To our knowledge, the relationships between evictions on both investor bargaining power and pricing in the same framework is an unexplored issue.

Our study makes three key contributions to the housing investment literature. First, we demonstrate that the racial composition of communities consistently influences investors' bargaining power. Beyond reaffirming the baseline bargaining advantage investors hold over owner-occupants, our findings show that investors systematically negotiate lower (higher) purchase (sales) prices in communities with a higher proportion of Black residents. This result represents an important contribution to the housing literature. Using the same bargaining framework, Ihlanfeldt and Mayock (2009) find that White sellers (buyers) obtain higher (lower) prices—by approximately 1 percent—when transacting with Black counterparts. While the magnitude of this disparity is modest, the authors suggest it reflects racial price discrimination. However, within their bargaining framework, an alternative interpretation is that one racial group, on average, outperforms another in negotiations, a claim that raises concerns when ascribed to entire racial groups based solely on skin color.

Our findings offer a different perspective from Ihlanfeldt and Mayock (2009) and Bayer et al. (2017). Instead of White participants discriminating against Black participants, our results suggest that the price effect is linked to investors, who—regardless of race—benefit from greater bargaining power in communities where Black residents constitute the majority. Importantly, we reach this conclusion only after controlling for home quality levels within Black communities, a factor consistently shown in the housing literature to be critical in explaining price outcomes.

Another key finding concerns the role of race in Other Nonwhite communities. We explicitly model Hispanic and Black communities, with White census tracts serving as the baseline comparison group. Based upon overall recent statistics for Los Angeles County, these three groups account for 80.4 percent of the population, while the largest remaining category is Asian (Non-

Hispanic), comprising 15.1 percent.[1] Within Other Nonwhite communities, our analysis reveals that investors obtain higher purchase prices and lower sales prices in these areas.

The second major contribution of our study is that socioeconomic and sociodemographic factors—specifically race, age, and education—provide deeper insight into home quality variations across communities. We find that majority-Black and majority-Other Nonwhite communities exhibit price declines in property quality relative to White areas, whereas majority-Latino communities see increases in property quality. Additionally, home quality levels rise in communities with higher education levels but decline in areas with higher median ages.

These refinements lead to our third contribution: demonstrating that socioeconomic and sociodemographic characteristics, along with eviction data, explain most of the base home quality effect routinely documented in the housing investment literature. Prior studies (Allen et al., 2018; Mills et al., 2019; Turnbull and van der Vlist, 2022; Cohen and Harding, 2023; Hayunga and Munneke, 2024) consistently find that investors acquire lower-quality properties at lower prices, a characteristic known as the rental property discount. Our results indicate that incorporating socioeconomic and sociodemographic characteristics explains most of this discount. Beyond this fundamental insight, our approach provides an alternative empirical strategy for researchers working with public record datasets that lack detailed transaction characteristics, such as financing terms, foreclosure status, and tenure—factors previously shown to influence price outcomes (Hayunga and Munneke, 2021).

Finally, while many individual interaction terms involving evictions are not statistically significant in our analyses, their inclusion meaningfully alters the overall estimates. In addition to

[1] The Other Nonwhite category includes individuals identifying as Two or More Races (Non-Hispanic), comprising 3.5 percent of the population in Los Angeles County, as well as those classified under Other Races, accounting for 1 percent.

rendering the base rental property discount statistically insignificant, controlling for eviction interactions materially reduces the estimated investor bargaining advantages. Furthermore, since evictions represent an exogenous shock linked to investor behavior, our framework provides a model for analyzing how other exogenous shocks—such as natural disasters or economic downturns—affect investor decision-making. This approach is particularly relevant in a market like Los Angeles, where housing shocks, including the impact of recent wildfires, and investor activity can be prominent.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the theoretical and empirical frameworks. Section 4 describes the data and presents descriptive statistics. Section 5 discusses the empirical results. Section 6 concludes.

2. Literature Review

The literature on investment in residential real property has experienced significant growth in recent years. One focal point of this research has been the involvement of large institutional investors like Blackstone around the Great Recession, which has been explored by Haughwout et al. (2011), Mills et al. (2019), Lambie-Hanson et al. (2020), Brunson (2020), Smith and Liu (2020), and D'Lima and Schultz (2022). Billings and Soliman (2024) analyze the impact of institutional investors purchasing single-family homes and converting them into permanent rentals, shedding light on racial gaps in homeownership and wealth.[2]

[2] Also focusing on the economic effects of real estate investors around the Great Recession, Garriga et al. (2023) find new results about small- and medium-sized investors. Other housing investment articles include Chinco and Mayer (2016) and Cvijanović and Spaenjers (2021) who delve into the behaviors of second-home buyers, while Bayer et al. (2021) examine investor contagion. The literature also examines the activities of speculators engaged in short-term transactions, as in the studies by Fu and Qian (2014), Fu et al. (2016), Bayer et al. (2020), and DeFusco et al. (2022).

Another important dimension of literature on housing investment investigates the outcomes of owner occupants compared to other market participants, including professional investors who establish entities such as Limited Liability Corporations (LLCs), individual investors, iBuyers, real estate agents, estates of deceased individuals, and public entities like the US federal government. Works within this domain include Rutherford et al. (2005), Levitt and Syverson (2008), Hayunga and Munneke (2021), Cohen and Harding (2023), Seiler and Yang (2023), and Hayunga and Munneke (2024).

A notable opportunity within this research examining negotiation power is the potential variability of intra-city bargaining effects, particularly in smaller areas characterized by diverse socioeconomic and sociodemographic characteristics. Our study aims to address this gap by leveraging the framework proposed by Harding, Rosenthal, and Sirmans (2003) (hereafter HRS). The HRS (2003) framework is particularly useful because it acknowledges the evolving awareness among housing economists that any study on investment in residential real estate must account for the distinct demand patterns between various market participants (Hayunga and Munneke 2021; Turnbull and van der Vlist 2022; Cohen and Harding 2023; and Hayunga and Munneke 2024).

For example, compared to investors, owner-occupiers demonstrate different taste preferences and utility functions. Additionally, owner-occupiers may seek to hedge against rental price volatility, a factor typically not considered by investors. Rental properties can also be lower quality due to excessive wear and tear by tenants and deferred maintenance by landlords. Turnbull and van der Vlist (2022) characterize these disparities as the rental property discount. Due to these differences, we use the HRS (2003) framework as the cornerstone of our analyses because it separately estimates the bargaining and demand (property quality) effects.[3]

[3] Turnbull and van der Vlist (2022) utilize a propensity score approach to mitigate selection bias arising from missing demand effects. However, Cohen and Harding (2023) advocate for the HRS (2003) approach, which separately

Using the variation within localized geographic areas, we can explore the interaction of the four important socioeconomic and sociodemographic dimensions of homeownership: income, race, age, and education. While there is a dearth of research on bargaining in the housing market concerning income, age, and education, the relationship between race and base homeownership has been studied.[4] Hermann (2023) offers one aspect through an analysis of American Community Survey (ACS) data, revealing substantial disparities in homeownership rates between Black and White populations in California from 2015 to 2019. Recent studies explain various contributing factors to this phenomenon, including mortgage-lending discrimination (Bartlett et al., 2022), discriminatory property taxation systems (Avenancio and Howard, 2022; Berry, 2021), and the impact of adverse regional racial climates, as evidenced by Google Trends data tracking searches for racially charged incidents of police brutality (Harris and Yelowitz, 2018).

These findings prompt our inquiry into whether investors strategically concentrate their activities in intra-city communities with higher minority populations, potentially capitalizing on bargaining advantages when acquiring single-family residential properties. Using the HRS (2003) framework, Ihlanfeldt and Mayock (2009) reveal price disparities between Black and White homeowners. Similarly, Bayer et al. (2017) explore the intersection of housing transaction prices with race, finding that Black residents pay approximately two percent more than White residents, though their analysis lacks a singular explanation. Prior to these studies, HRS (2003) includes some investigation of bargaining outcomes between Black and White homeowners using their bargaining model, yet their insights are limited by a scarcity of transactions.

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estimates bargaining and demand effects. Accordingly, our study prioritizes the examination of bargaining effects, aligning with the methodology outlined by HRS (2003).

[4] While HRS (2003) investigate how income, age, and education influence bargaining outcomes at the individual transaction level, our study extends this analysis to the community level. By examining socioeconomic and sociodemographic factors at the census tract level, we identify how these characteristics shape aggregate bargaining behavior among investors, offering insights into market-wide patterns that individual transaction studies may overlook.

Prior to discussing the HRS (2003) model that facilitates our analysis in the next section, the final area of literature we mention pertains to evictions. Notable contributions in this field include Desmond (2012), Desmond and Kimbro (2015), Desmond et al. (2015), and Desmond (2016). Among more recent studies, Collinson et al. (2024) examine the determinants, consequences, and socioeconomic impacts of evictions, while Coulson et al. (2025) estimate the relation between strict landlord regulation, evictions, and several other housing affordability outcomes. Their findings highlight an important trade-off between tenant protections and rent affordability: imposing strict landlord regulations may protect tenants from potential hardships associated with eviction, but at the cost of lower housing affordability and vacancy, and increased homelessness. While our study utilizes these studies as a component of our empirical framework, our analysis does not focus on the general outcomes of tenant removals. Rather, we examine the relation between socioeconomic and sociodemographic characteristics and investor bargaining advantages and rental property discount, while controlling for evictions as an exogenous shock.

3. Theory and Empirical Framework

This section describes the theoretical and empirical structures that guide our investigation. Section 3.1 details the HRS bargaining theory adapted to include our variables of interest. Section 3.2 details the empirical modeling considerations.

3.1 Theoretical Model

We use the bargaining model of HRS (2003), which is based on the fundamental hedonic housing price framework first popularized by Rosen (1974). The model begins with the standard hedonic model in Equation (1) that adds a bargaining component:

$$P_i = s'C_i + B_i\ , \tag{1}$$

where P_i is the natural logarithm of sale price of house i, C_i are the housing characteristics, and s is the vector of parameter estimates on these characteristics. The variable B_i is the bargaining effect for a particular house i. When there are lower (higher) prices because a buyer has more (less) bargaining power over a seller, B_i is negative (positive).

HRS (2003) show that if there are unobserved housing characteristics, the bargaining effect estimates will be lumped together with the demand effect estimates. To address this concern, they impose two assumptions that enable disentangling of the bargaining effects from the demand effects. Specifically, HRS (2003) assume B_i depends on buyer and seller demographic characteristics, D, each with coefficients b (dropping the subscript i to simplify notation) [5]:

$$B = b^{sell}D^{sell} + b^{buy}D^{buy} + e_B\ , \tag{2}$$

with e_B being a regression residual term. Substituting (2) into (1) yields (again suppressing the subscripts, i):

$$P = s'C + b^{sell}D^{sell} + b^{buy}D^{buy} + e_B\ . \tag{3}$$

HRS (2003) demonstrate that if one disentangles C into the observed characteristics, C_1, and the unobserved characteristics, C_2, one expects that:

$$s_2'C_2 = d^{sell}D^{sell} + d^{buy}D^{buy} + e_D\ , \tag{4}$$

where s_2 is the set of implicit prices on the unobserved characteristics, D^k is the same vector of individual descriptive characteristics (i.e., buyer or seller) as in Equation (2), and e_D is an *iid* error term. Equation (4) shows that if the unobserved characteristics are omitted from (3) then d^{sell} and d^{buy} will be biased measures of bargaining power. Substituting (4) into (3) yields:

[5] In their analyses, HRS (2003) and Cohen and Harding (2023) use D as indicator variables for whether a sale involves an investor. Our generalization in this paper allows for interactions of investor status (D) with racial/ethnic demographics (R), as the product of D and R, as in Equation (2') below.

$$P = s_1'C_1 + (b^{sell} + d^{sell})D^{sell} + (b^{buy} + d^{buy})D^{buy} + \varepsilon\,, \tag{5}$$

where s_1 is the set of implicit prices for the observed characteristics, and $\varepsilon = e_B + e_D$.

Hedonic housing price regressions typically include some unobservable housing characteristics. In this situation, by including dummy variables for investor buyer ($D^{buy} = 1$ if a transaction had an investor buyer, and $D^{buy} = 0$ otherwise) and investor seller ($D^{sell} = 1$ if a transaction had an investor seller, and $D^{sell} = 0$ otherwise) in a hedonic regression, it will be impossible to distinguish the bargaining effects for each type of investor from the demand effects. To address this issue, HRS (2003) impose two assumptions. Note that the bargaining effects are given by b^{sell} and b^{buy}, and the demand effects are given by d^{sell} and d^{buy}. Then, the first assumption of HRS (2003) is that there is symmetric bargaining power (i.e., $b^{sell} = -b^{buy}$), which implies an investor is equally skilled at purchasing and selling properties. Second, there are symmetric demand effects (i.e., investors buy and sell lower quality houses, $d^{sell} = d^{buy}$), which is more problematic. However, Cohen and Harding (2023) demonstrate that a more reasonable generalization of this assumption has no impact on the bargaining effect estimates.[6] HRS (2003) and Cohen and Harding (2023) note that these two assumptions lead to the following simplification of (5), where b is the bargaining effect and d is the demand effect:

$$P = s_1'C_1 + b(D^{sell} - D^{buy}) + d(D^{sell} + D^{buy}) + \varepsilon\,. \tag{6}$$

Therefore, the regression in Equation (6) leads to estimates of the bargaining effect, *b,* that imply the sign and significance of the bargaining effects of each type of investor.

As discussed above, a key contribution of this paper is to test the hypothesis that there are different investor bargaining effects estimates in communities with majority minority populations, high incomes, and higher education. Given that *D* is intended to encompass the presence of

[6] Given our primary emphasis on the estimation of bargaining effect estimates, our attention is directed towards modeling Equation (6).

investors in communities with differing demographics, including racial and ethnic demographics, i.e. for the case where there are three demographics groups, we rewrite (2) as:

$$B = b^{sell}D^{sell} + b^{sell,1}D^{sell}\, R_{sell,1} + b^{sell,2}D^{sell}\, R_{sell,2} + b^{sell,3}D^{sell}\, R_{sell,3} + b^{buy}D^{buy} + b^{buy,1}D^{buy}\, R_{buy,1} + b^{buy,2}D^{buy}\, R_{buy,2} + b^{buy,3}D^{buy}\, R_{buy,3} + e_B\,, \tag{2'}$$

In Equation (2'), $R_{sell,k}$ ($R_{buy,k}$) are the percentages of sellers (buyers) of race/ethnicity k in a property's census tract. The interaction of each D^{buy} with each $R_{buy,k}$ (and each D^{sell} with each $R_{sell,k}$) essentially is a different type of investor for each race/ethnicity, k. This generalization of HRS (2003) enables one to test the hypothesis that the investor bargaining effects are different across intra-city communities with different racial/ethnic makeups. For instance, we can address the question, are the bargaining effects for investors different when there are more minority residents in a neighborhood? We test the hypothesis that in communities with more of one specific demographic group, the bargaining effects are different than in communities with more than 50 percent of one specific demographic group. The three racial/ethnic groups we consider are percent Black, percent Hispanic/Latino (of any race), and percent Other racial minority.

Before we implement the estimation in (2'), we must address the potential concern with the omitted characteristics that HRS (2003) have considered in the special case where investors bargaining effects are homogeneous in communities with differing residential demographics. If we assume that investor buyers and investor sellers are equally skilled at bargaining within each type of neighborhood (i.e., $b^{buy,\mathrm{k}} = b^{sell,\mathrm{k}} = b^k$), an investor can bargain equally effectively as a buyer and a seller in communities with majority black population; it can bargain equally effectively as a buyer and a seller in majority Latino population communities; etc. In addition, if we assume demand effects are symmetric[7] for buyers and sellers when population within one specific demographic group changes, then Equation (6) becomes:

$$P = X\beta + b(D^{sell} - D^{buy}) + \Sigma_k b^k R_k (D^{sell} - D^{buy}) + d(D^{sell} + D^{buy}) + \Sigma_k d^k R_k(D^{sell} + D^{buy})$$

$$+ \tau_t + \theta_i + e_{it} . \qquad (6')$$

In Equation (6'), τ_t are sale date fixed effects and θ_i are Census tract fixed effects. Note that $X\beta$ in Equation (6') is equivalent to $s_1'C_1$ in Equation (6), which represents the product of the observed characteristics X and the corresponding parameter estimates, β. Here, X is a matrix of observed housing characteristics. For the race/ethnicity regressions, $k = 3$, i.e., each of the R_k represent indicators for majority population in the tract being Black, Latino, and other Nonwhite, respectively. Consequently, the parameter estimates for b^1, b^2, and b^3 are the unique investor bargaining effects for the interaction with each of these racial/ethnic indicators. For the median age regressions, $k = 1$ and the parameter estimate for b^1 is the bargaining effect for the interaction with median age. For the higher education variables, $k = 1$ and the parameter estimate for b^1 is the bargaining effect for the interaction with higher education.

3.2 Empirical Model

Equation (6') enables us to discern the impact of demographic factors on bargaining outcomes. Because the convention in HRS (2003) is *Seller – Buyer*, a positive coefficient on b^k signifies that investor buyers pay less while investor sellers receive more in transactions within demographic group k. Before implementing Equation (6'), we address three empirical issues. The first consideration pertains to the interdependence between expected transaction prices and

[7] The analysis of Cohen and Harding (2023) regarding the demand effect assumption generalization holds here as well. That is, if we relax the demand effect assumption to some extent, this has no effect on the bargaining effect estimates, so we proceed with estimating Equation (6).

anticipated marketing periods. As shown in prior research (Krainer, 2001), it is well known that prices and Time on Market (TOM) are outcomes that are jointly determined in housing transactions. For instance, pricing significantly impacts TOM, while properties listed below the expected market value often experience expedited sales, particularly as the price decreases. Consequently, transaction prices are recognized as a definitive endogenous factor influencing the duration a property remains on the market.

Similarly, TOM exerts a significant influence on home prices. Prolonged TOM may evoke negative perceptions among potential buyers, who could interpret a property as overpriced or as a stale listing, potentially leading to lower sales prices. Moreover, the housing market functions as a search and matching mechanism, necessitating sellers to await buyers with suitable reservation prices to initiate transactions. Therefore, sellers aiming for higher selling prices should anticipate an extended time on the market. Hence, TOM is also intrinsically linked to prices, establishing it as an endogenous factor in the housing market. To properly model both outcomes, our specifications use a system of simultaneous equations. To address the likely correlation between the error terms in the price and TOM equations, we utilize three-stage least squares (3SLS) estimation. While the first and second step are similar to a 2SLS regression, we apply Generalized Least Squares (GLS) to transform the variables.[8] Compared to two-stage least squares, 3SLS estimators remain consistent when correlation exists between the error terms, thereby providing more efficient estimates.

The second econometric consideration pertains to the fact that price and TOM are generally determined by the same set of right-hand-side variables, potentially leading to an under-identified system (Turnbull and Zahirovic-Herbert, 2012). To resolve this, we adopt the method proposed by

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[8] Note that we do not show the first and second step in our tables on the regression results. However, these results are available on request.

Turnbull and Dombrow (2006, 2007), creating two new independent variables. These variables account for the overlapping days that house listings share and the distance between them. The number of homes for sale within a small spatial area surrounding the subject home being modeled often results in localized competition and shopping externality effects. Local competition arises when an increased number of homes for sale intensifies the competition among sellers for potential buyers in the neighborhood, potentially reducing the probability of achieving a higher-priced match within a given timeframe. Conversely, shopping externality occurs when a higher number of houses for sale attracts additional prospective buyers to the neighborhood, potentially increasing the likelihood of matching a particular house with a buyer.

Incorporating these two unique independent variables enables us to identify the system, which have been used in a variety of studies. Listing density (*LD*) denotes the average competition intensity per day on market, while market competition (*MC*) reflects the number of competing properties near the subject property, accounting for the overlap of their marketing periods. These variables also account for the distance between the subject and competing properties. Consistent with Turnbull and Dombrow (2006), we include all competing homes within one mile of the subject property.

Following Turnbull and Dombrow (2006), we set $L(i)$ and $S(i)$ to be the listing date and end-of-listing date for property i. The overlapping number of days with other properties j is defined as:

$$O(i,j) = \min\big(S(i), S(j)\big) - \max\big(L(i), L(j)\big) + 1$$

The variable $D(i,j)$ is the straight-line distance between properties i and j. The two variables are computed as:

$$\text{Market competition}_{\text{i}} = \sum_{j \in I} \big(1 - D(i,j)\big)^2 O(i,j)$$

and

$$\text{Listing Density}_{\text{i}} = \sum_{j \in I} \frac{\left(1 - D(i,j)\right)^2 O(i,j)}{S(i) - L(i) + 1}.$$

With *LD* and *MC* providing unique determinants, we model the following system of equations using 3SLS:

$$\ln(P)_{ijt} = \alpha_1 + X'\beta_1 + Z'\psi_1 + \gamma ln(TOM)_{ijt} + \varphi ln(LD)_{ijt} + \lambda_{1,t} + \gamma_{1,i} + \epsilon_1, \tag{7}$$

$$ln(TOM)_{ijt} = \alpha_2 + X'\beta_2 + Z'\psi_2 + \delta P_{ijt} + \vartheta ln(MC)_{ijt} + \lambda_{2,t} + \gamma_{2,i} + \epsilon_2, \tag{8}$$

where P_{ijt} is the natural log of the price of house *i* that sold at time *t*, and *TOM* is the number of days on the market between the initial listing date and the sale date. The matrix *X* contains structural and transactional attributes (previously described as *C*), which also subsumes the *R* variables from Equation (6'). The matrix *Z* includes bargaining and demand effect terms, along with interactions involving demographics variables and the evictions increase indicator variables. Additionally, $\lambda_{1,t}$, $\lambda_{2,t}$ represent date-of-sale fixed effects, while $\gamma_{1,i}$, $\gamma_{2,i}$ capture spatial fixed effects, using the 88 incorporated cities in Los Angeles County as well as the other unincorporated municipalities, for a total of 305 spatial controls.

4. Data Sample

4.1 Data Collection and Data Cleansing

Our investigation focuses within Los Angeles County, an expansive metropolitan area comprising 88 incorporated municipalities and more than 100 unincorporated municipalities and accommodating over a quarter of California's population. With a population of approximately 10 million residents, Los Angeles County stands as the most populous county in the US, surpassing the populations of 41 individual US states.[9] Recognized for its cultural diversity, the county hosts

[9] https://worldpopulationreview.com/us-counties.

residents from over 140 countries, speaking more than 200 languages. The ethnic composition is diverse, with White (Non-Hispanic) comprising 26 percent of the population, Other Hispanic composing 22 percent, White Hispanic accounting for 18 percent, Asians representing 15 percent, and Black or African American (Non-Hispanic) constituting 8 percent.

To conduct our study, we gather and combine multiple datasets. We first obtain from the Los Angeles County Assessor's office three data extractions for October 23, 2017, September 18, 2019, and October 21, 2021. These data furnish details on all properties listed on the assessor's tax assessment rolls, along with their respective owners. Each extraction includes information on the owner of record at the specific extraction date, but not the buyers and sellers of transacted properties. However, by comparing data across two dates, we can deduce the sellers and buyers of all properties transacted during that period, based on ownership changes. There is also information on the previous three sales, so we restrict our attention to properties that sold only once during the intervals between each data extraction (i.e., once between October 2017 and September 2019 or once between September 2019 and October 2021). This ensures we are observing the names and mailing addresses of both the buyers and sellers, which is crucial for our algorithm to determine the investor ownership status.

To begin assembling the test sample, we merge the three assessor downloads based on each property's unique Assessor ID Number, resulting in a consolidated dataset containing 2,425,874 properties with valid Assessor ID Numbers. To eliminate duplicates of identical property transactions, we exclude homes without new trades between the download periods. However, repeat sales of the same property address are retained in the dataset, with previous sales prices and dates recorded as separate variables.

We proceed by applying a series of filters to eliminate erroneous data and ensure the generalizability of our findings to the typical housing market. We first delete properties not classified as residential 1–4-unit homes. This process removes properties with more than four units, vacant land, non-residential use codes, properties with religious or welfare tax exemptions, and condo buildings (i.e., those with more than four house numbers at a single street address). We also delete those with excessively high values exceeding $50 million. Following this filtering, 1,943,735 residential structures remain in the dataset. We next exclude transactions presumed to involve non-arms-length arrangements. This designation is applied to properties where the most recent transaction amount is either less than $50,000 or less than 5% of the second-most-recent transaction amount. After implementing these criteria, 1,357,302 properties remain in the dataset. We also remove an additional 10,834 properties from the final sample due to ambiguous ownership in 4Q2021.

The next step in assembling the sample is to append the TOM values. The TOM data come from iLeads, which originates from the local MLS. We merge the TOM using the address of each home with the data from the Los Angeles County Assessor. To generalize our findings to a market with properly motivated owners, we remove observations when the time for a seller to match with a buyer exceeds 365 days. At this point, we also require homes to have at least one bedroom and one bathroom, and not have less than 500 square feet of living area. Due to the limited availability of TOM data, the final sample consists of 62,574 observations.

Primary variables in our models include the number of bedrooms and bathrooms. We observe some properties have many of one or both (e.g., 16 bathrooms). We do not randomly remove these properties as they can be valid observations. Instead, we set an indicator value equal to one (and zero otherwise) when a particular property exhibits *Many Beds* or *Many Baths*.

Conditional on the owner type, these two indicator variables generally control for the upper 1–4 percent of their respective distribution.[10]

The refined sample is then geocoded to 2020 U.S. census tracts, comprising 2,470 unique tracts. To incorporate the tract-level demographic information, we append data from the 2020 ACS 5-year survey and the 2020 decennial census. For each of the 2,470 census tracts in our study area, we define *Higher Education* as a continuous variable based upon the percentage of tract residents with college or advanced degrees. We additionally derive two continuous variables denoting the *Median Income* and *Median Age* for each census tract, rounded to the nearest integer.

We also construct four binary variables using race/ethnicity categories derived from the 2020 decennial census. We set the indicator variable equal to one when the race/ethnicity is greater than 50 percent within a particular census tract. The categories are: 1) *Black* indicating the Black, non-Hispanic/Latino population; 2) *Latino*, representing households of Hispanic/Latino origin, irrespective of race; 3) *Other Nonwhite* indicates other nonwhite racial groups that are predominately Asian (Non-Hispanic); with 4) *White*, non-Hispanic/Latino serving as the reference category.

We next classify buyers and sellers into professional investors, individual investors, and owner-occupiers. The literature employs several methods to define investors, each with their trade-offs. Turnbull and van der Vlist (2022) identify investors as those not claiming the homestead exemption, while Hayunga and Munneke (2024) categorize investors based on transaction volume, identifying those with higher activity levels as investors. To ensure consistency with a published method, we adopt the approach used by Cohen and Harding (2023). Professional investors are those with owner names containing institutional identifiers such as "LLP," "Inc," "Invest," "Corp,"

[10] This approach follows Hayunga and Munneke (2024), among others in this literature.

and similar terms, as outlined in Cohen and Harding (2023). Individual investors are defined as non-professional investors who own more than four 1–4-unit residential properties at any given point across the three extractions of the assessor data.

A caveat regarding the individual-investor data lies in the strict criteria we use for their identification. To classify individuals as investors, we require ownership of a minimum of four properties at the given time, with an individual defined through an exact name-mailing address textual match. While this approach will lead to an undercount of the total number of individual investors, we prioritize robustness over potential overcounting. This choice mitigates the risk of inaccuracies inherent in employing a name-only match (e.g., counting all properties owned by individuals with a common name like "John Smith") or a fuzzy textual match. Due to the limited number of individual investors meeting the criterion, we do not detail separate regression models in our results below.

In the last step of our sample preparation, we perform a spatial join of the eviction data with each house location. This process enables us to associate, for each house and the month it sold, the month-to-month variation in the number of evictions linked to that within the corresponding court district. The evictions data is from the Anti-Eviction Mapping Project, which covers the twelve Los Angeles County court districts from February 2019 through February 2021. For reference, Figure 1 displays the boundaries of the twelve court districts.

[**Figure 1** about here]

Los Angeles County combines the data for the North Central and Northeast districts, so our analyses use eleven time series of eviction changes. To incorporate the information into our models, we set an indicator variable to one if evictions increase since the previous month and zero otherwise. We then assign this indicator to each house that sells in the respective court district.

Out of 264 changes across eleven districts and 24 months, there are only four instances (1.5 percent) when there is no change in the number of tenant removals across two months. Therefore, a value of one for the indicator variable represents eviction increases while a zero largely denotes a decrease in tenant dispositions.

[**Figure 2** about here]

In Figure 2, we present eviction levels across the eleven districts. Following the onset of the COVID-19 pandemic in early 2020, there is a noticeable decline in evictions, driven by the implementation of eviction moratoriums. On March 27, 2020, an executive order was issued establishing a statewide moratorium on evictions for renters affected by COVID-19, effective through May 31, 2020. This order prohibited landlords from evicting tenants for nonpayment of rent and barred enforcement of such evictions by law enforcement or courts.

Subsequently, on August 31, 2020, the COVID-19 Tenant Relief Act of 2020 (AB 3088) was signed into law, extending eviction protections for tenants experiencing financial hardship due to the pandemic. These protections remained in place until at least February 2021. This timeline aligns with the modest increases in eviction levels observed in Figure 2, although evictions do not return to their pre-COVID-19 levels through the end of our study period.

4.2 Descriptive Statistics

Table 1 presents descriptive statistics for our final sample, highlighting housing attributes and sociodemographic/socioeconomic characteristics. These statistics are segmented by owner type. The first set of columns details transactions involving professional investors as either buyers or sellers, followed by columns focusing on trades by individual investors. The final columns report sales exclusively involving owner-occupiers.

Each of the reported values aligns with expectations, except for the mean sale price among professional investors. Prior research on housing investment consistently identifies a rental property discount, yet the mean sale price of $1.71 million for the professional investor subsample appears inconsistent with this concept. However, this discrepancy is primarily driven by professional investors' greater share of multi-unit property acquisitions, which tend to be larger in square footage and transact at higher prices.

Notably, the maximum sale price in the professional investor category is $42.50 million—240 percent higher than the maximum for individual investors and 80 percent higher than the maximum for owner-occupiers. This alone contributes to the elevated mean sale price among professional investor transactions. Additionally, professional investors' preference for multi-unit properties results in larger average living area square footage compared to properties owned by individual investors or owner-occupiers, with mean sizes of 2,246, 1,904, and 1,869 square feet, respectively. Professional investor properties also tend to feature more bedrooms and bathrooms on average. As demonstrated in our regression analysis below, the data confirm the presence of a rental property discount for professional investors.

[**Table 1** about here]

Next, we present descriptive statistics separately for buyers and sellers across different ownership types. Prior research (Bayer et al., 2020; Hayunga & Munneke, 2024) suggests that investors primarily generate economic profits through property acquisition. To assess whether investor buyers acquire distinct properties, Table 2 presents summary statistics detailing the housing and socioeconomic/sociodemographic characteristics of buyers. While the mean suggests that professional investors purchase higher-valued homes than other market participants, this pattern is again attributable to their higher concentration of multi-unit property acquisitions, which are larger and transact at higher prices.

[**Table 2** about here]

Of further interest is the apparent preference of professional investors to purchase properties in census tracts exhibiting a greater percentage of residents with higher education. This observation is of interest because it might initially seem counterintuitive, given that higher educational attainment among homeowners typically signifies more expensive homes that may not align with typical investment properties. However, census tracts with a higher proportion of educated homeowners often signify desirable intra-city communities with potentially elevated property values. Housing investors, recognizing the stability and allure of such areas, may prioritize investments therein. Furthermore, the inclination to buy properties in areas with higher-educated homeowners suggests a possible perception that tenants within these census tracts are more reliable, likely to fulfill rental obligations promptly, and maintain the property adequately, thus mitigating risks associated with property damage or delinquency.

Table 3 presents descriptive statistics for sellers across different ownership types, revealing patterns akin to those observed previously. Differences in education levels are less pronounced when comparing professional investor sellers to non-investor sellers. Given the limited number of individual investor observations, this group is not analyzed separately in the below regression results. Instead, the following section presents our main estimates, distinguishing between two comparisons: (1) all investors (including individual investors) versus owner-occupiers and (2) professional investors versus owner-occupiers.

[**Table 3** about here]

5. Empirical Findings

This section presents the 3SLS regression results. In all tables, the "All Investors" specification codes the Seller (Buyer) indicator as 1 if the market participant is either an individual or professional investor, and 0 if an owner-occupier. The "Professional Investors" specification assigns a value of 1 only if the participant is a professional investor, and 0 otherwise (i.e., an owner-occupier or individual investor). As a result, the sample size remains consistent across specifications.

Prior to turning to specific regression estimates, we note that several alternative model specifications were tested but are not reported in separate tables. A key insight from these unreported models is the importance of including tract-level socioeconomic and sociodemographic controls. When such variables are omitted, the coefficient on the demand effect becomes positive, contradicting the expected rental discount. To ensure robust and interpretable results, all reported models include tract-level controls for race and ethnicity, median age, and educational attainment.

5.1 Baselines

Table 4 presents baseline results from our system of equations. This specification includes the bargaining and demand components, tract-level demographic characteristics, and district-level changes in eviction rates. Interaction terms are also included to estimate the marginal effects of eviction increases and neighborhood characteristics on both the bargaining and demand functions.

The base *Bargaining Effect* yields a coefficient of 0.1600 in Model 1 and 0.1530 in Model 2. Using the (Seller – Buyer) convention from Equation (6'), these statistically significant coefficients imply that investors purchase homes at prices roughly 16 percent below those paid by non-investors and sell them at prices around 16 percent above those received by non-investors. This symmetric effect aligns with the assumptions in the HRS (2003) framework and mirrors results from Bayer et al. (2020) and Cohen and Harding (2023), both of whom use similar public records data. Subsequent specifications further refine these baseline estimates.

[**Table 4** about here]

Turning to the *Demand Effect*, we observe a negative and statistically significant coefficient. This result is consistent with expectations and suggests that investors disproportionately transact in lower-class or lower-quality properties—at prices approximately 9 percent below those of non-investors. These results are consistent with findings from Turnbull and van der Vlist (2022), Cohen and Harding (2023), and Hayunga and Munneke (2024).

Most control variables are significant across both models in Table 4 and continue to be so in subsequent specifications. For example, racial composition at the census tract level meaningfully affects transaction prices. Properties in majority-Black tracts trade at an 8 percent discount across all models. Conversely, properties in majority-Latino tracts command premiums of approximately 4.5 percent, while tracts with higher concentrations of Other Nonwhite residents exhibit price premiums of 7–8 percent. Additionally, tracts with higher educational attainment consistently show transaction price increases of roughly 1.2 percent.

Interaction terms provide further insights. Investors gain additional bargaining advantages in majority-Black neighborhoods but experience diminished negotiating power in tracts with higher proportions of Other Nonwhite residents. These findings differ from the interpretation in Ihlanfeldt and Mayock (2009), who emphasized racial differences in bargaining ability. Our results instead suggest that observed disparities arise from investor behavior shaped by neighborhood context, not from participants' skin color alone.

Sociodemographic characteristics also shape the demand effect. We find that investor-traded properties in majority-Black and Other Nonwhite tracts exhibit deeper price discounts, while properties in majority-Latino tracts appear to be of higher class. Education levels also interact significantly with the demand component, indicating that investors' property preferences are sensitive to neighborhood educational attainment.

Finally, we examine the role of district-wide eviction activity. The eviction rate variable isolates broader market effects beyond tract-level variation. It likely captures investor concerns over tenant stability, rental income volatility, investor risk exposure, and broader social externalities such as crime. Results show that an increase in district-wide evictions from the prior month is associated with a 1.5 percent decline in average transaction prices. This result is consistent with the finding that rising evictions are associated with increased homelessness and hospital visits, and reduced earnings, durable goods consumption, and access to credit (Collinson et al. (2024)), in the sense that perhaps some of these detrimental socioeconomic changes are capitalized into house prices.

To better isolate the role of income from other tract characteristics, we next introduce median income independently in the models presented in Table 5. This helps address concerns about multicollinearity with race, age, and education variables. The Table 5 models also estimate the marginal influence of income on both the bargaining and demand functions.

[**Table 5** about here]

The Table 5 results resemble those of Table 4 but with attenuated coefficients, suggesting that income absorbs some of the variation previously attributed to other variables. The *Bargaining Effect* declines to approximately 12 percent in both models, and the *Demand Effect* remains negative but slightly smaller in magnitude. Both *Median income* and its interactions with the bargaining and demand components are statistically significant.

5.2 Refined Interactions

Tables 6 and 7 incorporate a comprehensive set of interaction terms to capture heterogeneity in how eviction shocks influence transaction prices across neighborhood contexts. Specifically, we include all two- and three-way interactions between eviction increases, the bargaining and demand components, and tract-level socioeconomic and sociodemographic variables. Table 7 adds median income as a continuous moderator.

The rationale behind these refinements is that investor perceptions of eviction activity are likely shaped by neighborhood context. Interactions with racial composition may reflect enduring patterns of segregation and differential investor sentiment. Age distribution can signal residential stability, with older populations potentially dampening market reactions to tenant turnover. Income and education may indicate neighborhood resilience through mechanisms such as tenant protections, social capital, or access to credit.

[**Table 6** about here]

Table 6 shows that the *Bargaining Effect* remains strongly positive, confirming that investors consistently earn favorable price outcomes. The *Demand Effect* remains negative in Model 1 but loses significance in Model 2, suggesting that the expanded set of covariates and interactions may be absorbing variation previously attributed to investor preferences for lower-quality properties. Most covariates retain their expected signs and significance. Race, ethnicity, and education continue to shape the base and marginal effects. Investors exhibit enhanced bargaining power in tracts with higher shares of Black and Other Nonwhite residents, but reduced power in majority-Latino tracts.

Although most interactions involving the *Evictions Up* indicator are statistically insignificant, their inclusion alters the interpretation of the main eviction effect. Notably, the base coefficient on eviction increases is now positive and statistically significant. While initially counterintuitive, this shift reflects the layered structure of the model. With higher-order interactions included, main effects no longer represent average marginal effects across all tracts, but rather the effect conditional on the reference group—majority White tracts with mean-centered income, age, and education. In this context, rising evictions may not reflect distress but rather market turnover or reinvestment opportunities in relatively stable areas.

To explore the role of income further, Table 7 includes median income along with the full set of interaction terms. As a proxy for household purchasing power and economic capacity, income typically exhibits more short-term variability than race, age, or education and serves as a strong predictor of housing affordability, demand, and investor appeal.

[**Table 7** about here]

Several important findings emerge from Table 7. First, the *Bargaining Effect* for professional investors declines to 0.0755, aligning with results from Hayunga and Munneke (2024), who leverage detailed transaction-level housing data. This consistency suggests that our identification strategy—using sociodemographic controls and their interactions—provides a viable alternative to datasets with richer property-level attributes.

Second, the *Demand Effect* becomes statistically insignificant across both models, indicating that observed differences in property type may now be fully accounted for by interactions among investor status, neighborhood characteristics, and eviction trends. This supports the argument that sociodemographic variables can proxy for unobserved housing features in models based on public records data.

Third, we observe a notable change in the role of *Evictions Up* × *Demand Effect*, which becomes a significant negative determinant of transaction prices. This interaction was also significant in Table 6 (Model 2 for Professional Investors) but was not present in Tables 4 or 5. This shift helps explain why the base *Evictions Up* coefficient becomes positive: the interaction term now captures the negative price impact associated with investor trade in lower-quality properties during periods of rising eviction activity, effectively absorbing what was previously reflected in the main effect.

6. Conclusion

This paper contributes to the growing literature on the impact of investors on single-family house prices in the U.S. focusing on Los Angeles County—an area with significant racial, ethnic, and socioeconomic diversity—we examine how investor bargaining and demand effects vary across census tracts with differing income levels, racial and ethnic compositions, educational attainments, and age demographics. To achieve this, we apply the bargaining model of Harding, Rosenthal, and Sirmans (2003), incorporating interactions between bargaining power, investor demand functions, socioeconomic and sociodemographic characteristics, and eviction trends. We also address the simultaneity of price and time on the market. This approach enables us to generate distinct estimates of bargaining and demand effects across neighborhoods with varying demographic and economic conditions while assessing their influence on investors' baseline bargaining power and demand functions.

Our findings reveal notable differences in investor bargaining power across sociodemographic groups. Investors exhibit a stronger bargaining advantage in census tracts with majority Black populations, acquiring properties at lower prices and selling at higher prices compared to owner-occupants. In contrast, in census tracts with higher proportions of Other Nonwhite residents, primarily comprised of Asians, owner-occupants demonstrate greater bargaining power.

Additionally, we incorporate a comprehensive set of interaction terms between eviction increases and key sociodemographic, bargaining, and demand factors. The results indicate that both the base bargaining and demand effects diminish in magnitude. The estimated bargaining effect aligns with prior studies utilizing more detailed housing transaction data, while the demand effect becomes statistically indistinguishable from zero. This suggests that incorporating sociodemographic, socioeconomic, and eviction characteristics provides an alternative empirical framework for researchers using public record datasets to examine investor bargaining outcomes.

References

Allen, M. T., Rutherford, J., Rutherford, R., and A. Yavas. (2018). "Impact of Investors in Distressed Housing Markets." *The Journal of Real Estate Finance and Economics*, 56, 622–652.

Avenancio-Leon, C. and T. Howard (2022). "The Assessment Gap: Racial Inequalities in Property Taxation," *Quarterly Journal of Economics*, 137(3), 1383–1434.

Bartlett, R., A. Morse, R. Stanton, R., and N. Wallace (2022): "Consumer-Lending Discrimination in the FinTech Era," *Journal of Financial Economics* 143(1), 30–56.

Bayer, P., C. Geissler, K. Mangum, and J. W. Roberts (2020): "Speculators and Middlemen: The Strategy and Performance of Investors in the Housing Market," *Review of Financial Studies* 33, 5212–5247.

Bayer, P., K. Mangum, and J. W. Roberts (2021): "Speculative Fever: Investor Contagion in the Housing Bubble," *American Economic Review* 111, 609–651.

Bayer, P., Casey, M., Ferreira, F., and McMillan, R. (2017). "Racial and ethnic price differentials in the housing market." *Journal of Urban Economics*, *102*, 91-105.

Berry, C. R. (2021): "Reassessing the Property Tax," Working Paper 3800536, SSRN.

Billings, S. B., and Soliman, A. (2023). The Erosion of Homeownership and Minority Wealth. *Available at SSRN 4649479*.

Brunson, S. (2020). "Wall Street, Main Street, Your Street: How Investors Impact the Single-Family Housing Market". University of North Carolina at Charlotte working paper.

Chinco, A. and C. Mayer (2016): “Misinformed Speculators and Mispricing in the Housing Market,” *Review of Financial Studies* 29, 486–522.

Cohen, J. P., and Harding, J. P. (2023). “The bargaining and contagion effects of investors in single family residential properties: The case of Denver Colorado,” *The Journal of Real Estate Finance and Economics*, 67(1), 29–64.

Collinson, R., Humphries, J. E., Mader, N., Reed, D., Tannenbaum, D., and Van Dijk, W. (2024). “Eviction and poverty in American cities,” *The Quarterly Journal of Economics*, 139(1), 57–120.

Coulson, N. E., Le, T., Ortego-Marti, V., Shen, L. (2025) “Tenant rights, eviction, and rent affordability,” *The Journal of Urban Economics,* https://doi.org/10.1016/j.jue.2025.103762

Cvijanović, D., and Spaenjers, C. (2021). “We’ll always have Paris: Out-of-country buyers in the housing market,” *Management Science*, 67(7), 4120–4138.

DeFusco, A. A., Nathanson, C. G., and E. Zwick. (2022). “Speculative Dynamics of Prices and Volume.” *Journal of Financial Economics*, 146(1), 205–229.

Desmond, M. (2012). “Eviction and the Reproduction of Urban Poverty,” *American Journal of Sociology*, 118(1), 88–133.

Desmond, M. (2016). *Evicted: Poverty and profit in the American city*. New York. Crown Publishers.

Desmond, M., Gershenson, C., and Kiviat, B. (2015). “Forced relocation and residential instability among urban renters,” *Social Service Review*, 89(2), 227–262.

Desmond, M., and Kimbro, R. T. (2015). “Eviction’s Fallout: Housing, Hardship, and Health,” *Social Forces*, 94(1), 295–324.

D'Lima, W., and Schultz, P. (2022). “Buy-to-Rent Investors and the Market for Single Family Homes,” *Journal of Real Estate Finance and Economics* 64, 116–152.

Fu, Y. and W. Qian (2014): “Speculators and Price Overreaction in the Housing Market,” *Real Estate Economics* 42, 977–1007.

Fu, Y., W. Qian, and B. Yeung (2016): “Speculative Investors and Transactions Tax: Evidence from the Housing Market,” *Management Science* 62, 3254-3270.

Garriga, C., Gete, P., and A. Tsouderou. (2023). “The Economic Effects of Real Estate Investors.” *Real Estate Economics*, 51(3), 655–685.

Harding, J.H., S.S. Rosenthal, and C.F. Sirmans (2003): “Estimating Bargaining Power in the Market for Existing Homes,” *Review of Economics and Statistics* 85, 178-188.

Harris, T. F., and A. Yelowitz (2018): “Racial Climate and Homeownership,” *Journal of Housing Economics* 40, 41–72.

Haughwout, A., Lee, D., Tracy, J. S., and W. Van der Klaauw. (2011). “Real Estate Investors, the Leverage Cycle, and the Housing Market Crisis.” *FRB of New York Staff Report*, (514).

Hayunga, D. K., and Munneke, H. J. (2021). “Examining Both Sides of the Transaction: Bargaining in the Housing Market,” *Real Estate Economics* 49(2), 663–691.

Hayunga, D. K., and Munneke, H. J. (2024). “Volume Traders of Non-Homogenous Assets,” *Journal of Real Estate Finance and Economics* forthcoming.

Hermann, A. (2023). “In Nearly Every State, People of Color are Less Likely to Own Homes compared to White Households”, *Housing Perspectives,* Joint Center for Housing Studies of Harvard University.

Ihlanfeldt, K., and T. Mayock (2009): “Price Discrimination in the Housing Market,” *Journal of Urban Economics*” 66(2), 125–140.

Krainer, J. (2001). “A Theory of Liquidity in Residential Real Estate Markets.” *Journal of Urban Economics*, 49(1), 32–53.

Lambie-Hanson, L, Wenli L, and M. Slonkosky. (2022). “Real Estate Investors and the US Housing Recovery,” *Real Estate Economics* 50(6), 1425–1461.

Levitt, S.D., and C. Syverson (2008): “Market Distortions when Agents are Better Informed: The Value of Information in Real Estate Transactions,” *Review of Economics and Statistics* 90, 599–611.

Mills, J., R. Molloy, and R. Zarutskie (2019): “Large-Scale Buy-to-Rent Investors in the Single-Family Housing Market: The Emergence of a New Asset Class,” *Real Estate Economics* 47, 399–430.

Rutherford, R.C., T.M. Springer, and A. Yavas (2005): “Conflicts between Principals and Agents: Evidence from Residential Brokerage,” *Journal of Financial Economics* 76, 627–65.

Seiler, M. J., and Yang, L. (2023). “The Burgeoning Role of iBuyers in the Housing Market,” *Real Estate Economics*, 51(3), 721–753.

Smith, P. S., and Liu, C. H. (2020). “Institutional Investment, Asset Illiquidity, and Post-Crash Housing Market Dynamic,” *Real Estate Economics* 48(3), 673–709.

Turnbull, G. K., and Dombrow, J. (2006). “Spatial Competition and Shopping Externalities: Evidence from the Housing Market.” *The Journal of Real Estate Finance and Economics 32*, 391–408.

Turnbull, G. K., and Dombrow, J. (2007). “Individual Agents, Firms, and the Real Estate Brokerage Process.” *The Journal of Real Estate Finance and Economics 35* 57–76.

Turnbull, G. K., and van der Vlist, A. J. (2022). “Bargaining Power and Segmented Markets: Evidence from Rental and Owner-occupied Housing,” *Real Estate Economics* 50(5), 1307–1333.

Turnbull, G. K., and Zahirovic-Herbert, V. (2012). “The Transitory and Legacy Effects of the Rental Externality on House Price and Liquidity.” *The Journal of Real Estate Finance and Economics* 44, 275–297.

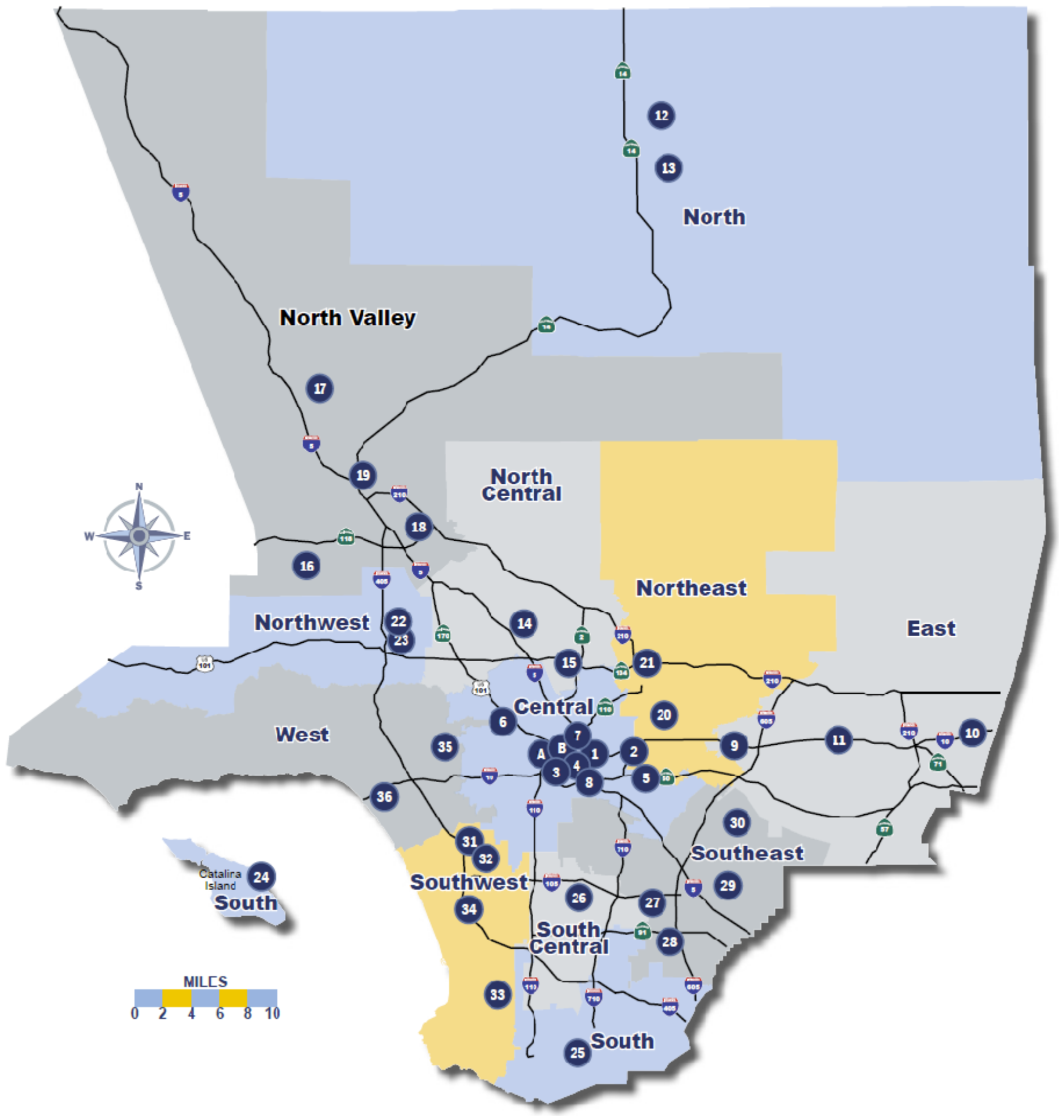

Figure 1. Los Angeles County Court Districts in 2023.
Source: https://www.lacourt.org/courthouse/pdf/districtmap2023.pdf.

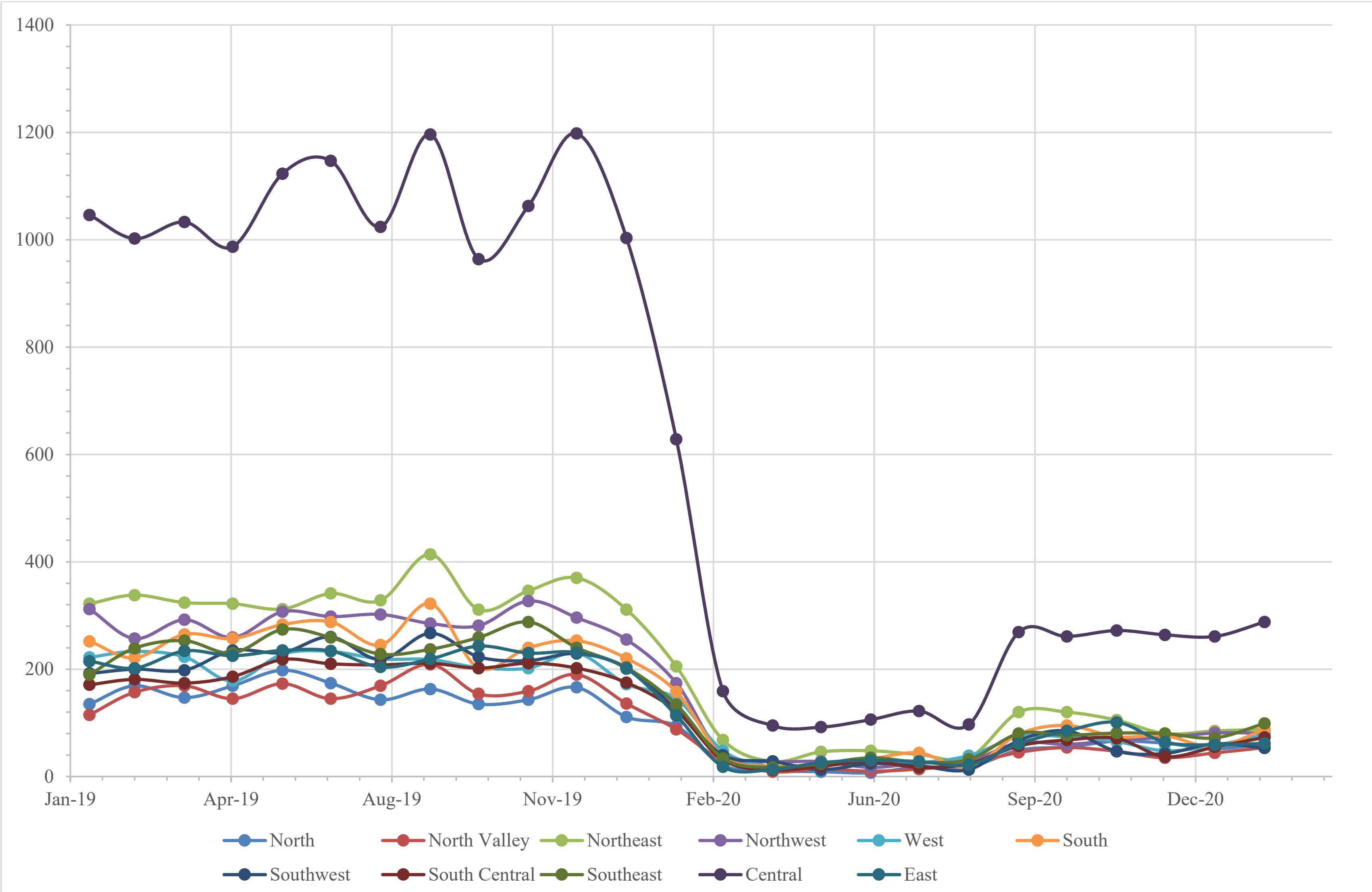

Figure 2: Monthly Eviction Levels by Los Angeles County Court District for the period is from February 2019 through February 2021. *Source*: Authors' tabulation from data at Anti-Eviction Mapping Project: https://antievictionmap.com/there-is-no-eviction-moratorium

Table 1: Descriptive Statistics by *Owner* Types, Los Angeles County

	Professional Investor Trades				Individual Investor Trades				Owner-Occupier Trades			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Panel A: Housing Attributes												
Sale Price ($Million)	1.71	2.46	0.08	42.50	1.07	1.29	0.12	12.50	0.91	0.78	0.05	23.60
Time On Market	101.69	76.74	1.00	365.00	89.02	71.55	4.00	350.00	77.84	60.85	0.00	365.00
Evictions	297.91	337.30	7.00	1,198.00	216.02	268.82	9.00	1,198.00	171.76	210.23	7.00	1,198.00
Listing Density	1.80	0.38	0.69	3.12	1.72	0.38	0.74	2.74	1.72	0.37	0.00	3.14
Market Competition	5.96	0.93	1.46	8.56	5.73	0.97	2.73	8.35	5.64	0.86	0.00	8.52
Bedrooms	3.55	1.52	1.00	16.00	3.38	1.50	1.00	10.00	3.28	1.00	1.00	17.00
Many Beds	0.04	0.19	0.00	1.00	0.04	0.19	0.00	1.00	0.01	0.08	0.00	1.00
Bathrooms	2.79	1.75	1.00	16.00	2.44	1.36	1.00	10.00	2.39	1.05	1.00	12.00
Many Baths	0.04	0.20	0.00	1.00	0.02	0.14	0.00	1.00	0.00	0.07	0.00	1.00
Units	1.19	0.62	1.00	4.00	1.23	0.64	1.00	4.00	1.04	0.27	1.00	4.00
SF Main	2,246	1,592	500	20,670	1,904	1,152	528	7,971	1,869	915	500	16,683
Lot Size (1,000 SF)	16.00	72.29	1.00	1,904.16	21.15	59.79	1.14	806.68	26.06	109.74	0.18	5,036.73
House Age	64.27	30.83	-2.00	135.00	61.90	27.36	0.00	125.00	55.75	25.18	-1.00	195.00
Panel B: Sociodemographic/Socioeconomic Characteristics												
Black	0.03	0.18	0.00	1.00	0.01	0.12	0.00	1.00	0.02	0.14	0.00	1.00
Latino	0.33	0.47	0.00	1.00	0.41	0.49	0.00	1.00	0.30	0.46	0.00	1.00
Other Nonwhite	0.05	0.21	0.00	1.00	0.06	0.24	0.00	1.00	0.07	0.26	0.00	1.00
Median Age	39.66	6.88	20.00	67.00	37.77	6.63	20.00	56.00	40.21	6.52	20.00	67.00
Higher Education %	42.28	24.30	1.40	88.00	33.88	22.60	2.20	86.70	39.03	20.22	1.40	88.00
Median Income ($1,000)	95.17	46.15	16.66	250.00	82.69	38.83	21.30	236.71	96.33	37.01	16.66	250.00
Observations	5,317				372				56,924			

Note: Spanning from 2019 to 2021, the table details the descriptive statistics for the housing attributes in Panel A and socioeconomic/sociodemographic variables in Panel B. *Sales Price* ($M) is the last sale amount as of 4Q2021. *Evictions* are the number of evictions reported by eleven court districts within L.A. County. *Units* indicate the number of units in the building, ranging from 1 to 4. *SF Main* is the square footage of the main living area rounded to an integer. *Lot Size* is the square footage of the lot in 1,000s. Since a small number of houses were rebuilt within a year or two after the purchase date, *House Age* includes a small number of negative values. Based upon 2020 census data, *Black*, *Latino*, and *Other Nonwhite* are binary variables set to one when the race/ethnicity is greater than 50 percent within a census tract, and zero otherwise. *Higher Education* is a continuous variable measuring the percentage of tract residents who hold a college or advanced degree. Additionally, each traded home is assigned the *Median Age* and *Median Income* (in $1000) corresponding to the census tract it occupies. *Sources*: Los Angeles County Assessor, the U.S. Census Bureau's 2020 American Community Survey, iLeads, and the Anti-Eviction Mapping Project: https://antievictionmap.com/there-is-no-eviction-moratorium.

Table 2: Descriptive Statistics by *Buyer* Types, Los Angeles County

	Professional Investor Buyer				Individual Investor Buyer				Owner-Occupier Buyer			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Panel A: Housing Attributes												
Sale Price ($Million)	1.93	2.93	0.09	42.50	1.17	1.35	0.12	12.50	0.94	0.88	0.05	32.30
Time On Market	96.12	78.46	1.00	364.00	83.96	69.03	4.00	341.00	79.24	61.91	0.00	365.00
Evictions	292.56	338.72	7.00	1,198.00	220.20	261.69	9.00	1,198.00	178.11	219.86	7.00	1,198.00
Listing Density	1.79	0.38	0.69	3.12	1.73	0.37	0.83	2.67	1.73	0.37	0.00	3.14
Market Competition	5.83	1.01	1.46	8.37	5.66	1.00	2.73	7.96	5.66	0.87	0.00	8.56
Bedrooms	3.55	1.62	1.00	14.00	3.45	1.47	1.00	10.00	3.29	1.03	1.00	17.00
Many Beds	0.05	0.22	0.00	1.00	0.04	0.20	0.00	1.00	0.01	0.09	0.00	1.00
Bathrooms	2.78	1.80	1.00	14.00	2.44	1.34	1.00	7.00	2.41	1.09	1.00	16.00
Many Baths	0.05	0.21	0.00	1.00	0.03	0.16	0.00	1.00	0.01	0.08	0.00	1.00
Units	1.27	0.73	1.00	4.00	1.21	0.64	1.00	4.00	1.04	0.29	1.00	4.00
SF Main	2,315	1,609	504	13,974	1,949	1,208	563	7,971	1,884	960	500	20,670
Lot Size (1,000 SF)	16.33	58.92	1.00	1,904.16	19.12	48.33	1.14	438.01	25.56	108.54	0.18	5,036.73
House Age	69.06	28.45	-1.00	132.00	64.02	25.41	0.00	117.00	55.97	25.58	-2.00	195.00
Panel B: Sociodemographic/Socioeconomic Characteristics												
Black	0.03	0.16	0.00	1.00	0.02	0.14	0.00	1.00	0.02	0.14	0.00	1.00
Latino	0.30	0.46	0.00	1.00	0.33	0.47	0.00	1.00	0.30	0.46	0.00	1.00
Other Nonwhite	0.05	0.22	0.00	1.00	0.06	0.24	0.00	1.00	0.07	0.25	0.00	1.00
Median Age	40.04	6.92	20.00	67.00	38.51	6.65	20.00	56.00	40.16	6.54	20.00	67.00
Higher Education %	45.60	24.12	1.40	88.00	38.45	22.28	3.70	86.70	39.03	20.43	1.4	88.00
Median Income ($1,000)	98.70	48.47	17.77	250.00	88.30	37.72	24.77	236.71	96.08	37.39	16.66	250.00
Observations	2,443				197				59,934			

Note: Spanning the period from 2019 to 2021, this table presents descriptive statistics for housing attributes in Panel A and socioeconomic/sociodemographic variables in Panel B. *Sales Price ($M)* represents the final sale amount as of the fourth quarter of 2021. *Evictions* denotes the count of evictions reported by eleven court districts within Los Angeles County. *Units* indicates the number of units within the building, ranging from 1 to 4. *SF Main* refers to the square footage of the main living area, rounded to the nearest integer. *Lot Size* is presented in thousands of square feet. Due to a small number of houses being rebuilt within a year or two after the purchase date, *House Age* includes a few negative values. Based on data from the 2020 census, *Black*, *Latino*, and *Other Nonwhite* are binary variables set to one when the respective race/ethnicity constitutes more than 50 percent of the population within a census tract, and zero otherwise. *Higher Education* is a continuous variable representing the percentage of tract residents holding a college or advanced degree. Each traded home is associated with the *Median Age* and *Median Income* (in $1000) corresponding to the census tract it occupies. *Sources*: Los Angeles County Assessor, the U.S. Census Bureau's 2020 American Community Survey, iLeads, and the Anti-Eviction Mapping Project: https://antievictionmap.com/there-is-no-eviction-moratorium.

Table 3: Descriptive Statistics by *Seller* Types, Los Angeles County

	Professional Investor Seller				Individual Investor Seller				Owner-Occupier Seller			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Panel A: Housing Attributes												
Sale Price ($Million)	1.75	2.69	0.08	42.50	0.97	1.23	0.17	11.00	0.94	0.88	0.05	26.10
Time On Market	108.80	76.59	2.00	365.00	93.75	73.81	8.00	350.00	78.35	61.52	0.00	365.00
Evictions	304.74	340.23	7.00	1198.00	211.43	275.04	9.00	1198.00	176.20	217.27	7.00	1198.00
Listing Density	1.81	0.37	0.69	3.03	1.72	0.39	0.74	2.74	1.72	0.37	0.00	3.14
Market Competition	6.08	0.86	2.71	8.56	5.80	0.91	3.23	8.35	5.64	0.87	0.00	8.52
Bedrooms	3.60	1.48	1.00	16.00	3.28	1.52	1.00	10.00	3.29	1.03	1.00	17.00
Many Beds	0.03	0.18	0.00	1.00	0.03	0.18	0.00	1.00	0.01	0.09	0.00	1.00
Bathrooms	2.89	1.80	1.00	16.00	2.42	1.38	1.00	10.00	2.40	1.08	1.00	13.00
Many Baths	0.05	0.21	0.00	1.00	0.01	0.11	0.00	1.00	0.01	0.08	0.00	1.00
Units	1.15	0.53	1.00	4.00	1.25	0.65	1.00	4.00	1.05	0.30	1.00	4.00
SF Main	2,323	1,693	500	20,670	1,842	1,081	528	6,670	1,882	943	500	16,683
Lot Size (1,000 SF)	15.96	79.46	1.09	1,904.16	23.13	70.02	1.20	806.68	25.67	108.23	0.18	5,036.73
House Age	59.85	32.77	-2.00	135.00	59.94	29.28	0.00	125.00	56.32	25.39	-1.00	195.00
Panel B: Sociodemographic/Socioeconomic Characteristics												
Black	0.04	0.18	0.00	1.00	0.01	0.07	0.00	1.00	0.02	0.14	0.00	1.00
Latino	0.35	0.48	0.00	1.00	0.48	0.50	0.00	1.00	0.30	0.46	0.00	1.00
Other Nonwhite	0.04	0.21	0.00	1.00	0.06	0.24	0.00	1.00	0.07	0.25	0.00	1.00
Median Age	39.41	6.86	20.00	67.00	36.90	6.51	26.00	54.00	40.20	6.54	20.00	67.0
Higher Education %	40.29	24.28	1.40	87.60	28.8	22.02	2.20	81.20	39.26	20.41	1.40	88.00
Median Income ($1,000)	93.33	45.18	16.67	250.00	76.22	38.91	21.30	228.84	96.36	37.44	16.67	250.00
Observations	3,121				178				59,275			

Note: This table spans the period from 2019 to 2021 and provides descriptive statistics for housing attributes in Panel A and socioeconomic/sociodemographic variables in Panel B. *Sales Price ($M)* denotes the final sale amount as of the fourth quarter of 2021. *Evictions* represents the count of evictions reported by eleven court districts within Los Angeles County. *Units* indicates the number of units within the building, ranging from 1 to 4. *SF Main* refers to the square footage of the main living area, rounded to the nearest integer, while *Lot Size* is presented in thousands of square feet. *House Age* may include a few negative values due to a small number of houses being rebuilt within a year or two after the sales date. Based on data from the 2020 census, *Black*, *Latino*, and *Other Nonwhite* are binary variables set to one when the respective race/ethnicity constitutes more than 50 percent of the population within a census tract, and zero otherwise. *Higher Education* is a continuous variable representing the percentage of tract residents holding a college or advanced degree. Each traded home is associated with the *Median Age* and *Median Income* (in $1000) corresponding to the census tract it occupies. *Sources*: Los Angeles County Assessor, the U.S. Census Bureau's 2020 American Community Survey, iLeads, and the Anti-Eviction Mapping Project: https://antievictionmap.com/there-is-no-eviction-moratorium.

Table 4: Base Bargaining and Demand Effects

	Ln(Sale Prices) All Investors	Ln(Sale Prices) Professional Investors
Bargaining Effect	0.1600*** (6.58)	0.1530*** (6.08)
Demand Effect	-0.0881*** (-3.81)	-0.0712*** (-2.96)
Black	-0.0790*** (-10.05)	-0.0796*** (-10.15)
Latino	0.0461*** (12.59)	0.0469*** (12.83)
Other Nonwhite	-0.0687*** (-10.73)	-0.0686*** (-10.74)
Median Age	-0.0003 (-1.33)	-0.0003 (-1.29)
Higher Education	0.0122*** (134.50)	0.0122*** (135.00)
Bargaining Effect x Black	0.1050*** (5.46)	0.0990*** (4.99)
Bargaining Effect x Latino	-0.0025 (-0.23)	-0.0031 (-0.27)
Bargaining Effect x Other Nonwhite	-0.0395*** (-2.67)	-0.0431*** (-2.80)
Bargaining Effect x Median Age	-0.0023*** (-3.74)	-0.0019*** (-2.97)
Bargaining Effect x Higher Education	-0.0004* (-1.80)	-0.0006** (-2.49)
Demand Effect x Black	-0.0646*** (-3.20)	-0.0637*** (-3.09)
Demand Effect x Latino	0.0559*** (5.41)	0.0504*** (4.64)
Demand Effect x Other Nonwhite	-0.0729*** (-5.17)	-0.0752*** (-5.11)
Demand Effect x Median Age	-0.0003 (-0.44)	-0.0006 (-1.00)
Demand Effect x Higher Education	0.0042*** (20.20)	0.0043*** (19.32)
Evictions Up	-0.0156*** (-7.97)	-0.0157*** (-8.04)
Evictions Up x Bargaining Effect	-0.0026 (-0.42)	-0.0009 (-0.15)
Evictions Up x Demand Effect	-0.0032 (-0.54)	-0.0034 (-0.55)
Ln(Time On Market)	-0.0279*** (-24.17)	-0.0280*** (-24.23)
Ln(Listing Density)	0.0838*** (59.57)	0.0836*** (59.42)

	Ln(Sale Prices) All Investors	Ln(Sale Prices) Professional Investors
Annual Fixed Effects	Yes	Yes
Spatial Fixed Effects	Yes	Yes
Number of Observations	65,151	65,151
R^2	0.860	0.860

Notes: This table reports 3SLS regression models spanning the years 2019 to 2021 for Los Angeles County, with the natural logarithm of transaction prices as the dependent variable. The convention on the *Bargaining Effect* is Seller minus Buyer while the *Demand Effect* is Seller plus Buyer. In the "All Investors" regression, the Seller (Buyer) indicators take value of 1 if the Seller (Buyer) is any type of investor (i.e., individual or professional). In the "Professional Investors" regression, the Seller (Buyer) indicators take value of 1 if the Seller (Buyer) is a professional investor. Due to the limited sample size of individual investors, those results are omitted. The race variables take the value of 1 if the racial composition for a particular census tract is greater than 50 percent. *Higher Education* is a continuous variable representing the percentage of census tract residents with a college or advanced degree. *Median Age* and *Median Income* correspond to the tract-level values associated with each traded home, based on the census tract in which the property is located. *Evictions Up* is an indicator equal to 1 for month-over-month increases in evictions in the court-district where a house sale is located, and 0 otherwise. The models include the additional housing characteristics noted in Tables 1 to 3. Spatial fixed effects control for over 300 municipalities. *T*-statistics are in parentheses with *, **, and *** denoting *p*-values less than 0.10, 0.05, and 0.01, respectively.

Table 5: Base Bargaining and Demand Effects with Income

	Ln(Sale Prices) All Investors	Ln(Sale Prices) Professional Investors
Bargaining Effect	0.1250*** (5.02)	0.1160*** (4.48)
Demand Effect	-0.0677*** (-2.83)	-0.0515** (-2.07)
Black	-0.0767*** (-9.82)	-0.0772*** (-9.91)
Latino	0.0417*** (11.40)	0.0423*** (11.61)
Other Nonwhite	-0.0653*** (-10.25)	-0.0653*** (-10.25)
Median Age	-0.0006*** (-2.79)	-0.0006*** (-2.78)
Higher Education	0.0118*** (107.96)	0.0118*** (108.43)
Median Income ($\times$-10^3)	0.0002*** (3.74)	0.0002*** (3.65)
Bargaining Effect x Black	0.1010*** (5.27)	0.0959*** (4.87)
Bargaining Effect x Latino	0.0080 (0.75)	0.0083 (0.74)
Bargaining Effect x Other Nonwhite	-0.0449*** (-3.04)	-0.0480*** (-3.13)
Bargaining Effect x Median Age	-0.0013** (-1.99)	-0.0008 (-1.21)
Bargaining Effect x Higher Education	0.0002 (0.58)	0.0000 (0.15)
Bargaining Effect x Median Income ($\times$-10^3)	-0.0003** (-2.56)	-0.0003*** (-2.82)
Demand Effect x Black	-0.0658*** (-3.28)	-0.0665*** (-3.25)
Demand Effect x Latino	0.0513*** (4.92)	0.0452*** (4.11)
Demand Effect x Other Nonwhite	-0.0727*** (-5.17)	-0.0753*** (-5.13)
Demand Effect x Median Age	-0.0006 (-1.02)	-0.0009 (-1.48)
Demand Effect x Higher Education	0.0043*** (16.60)	0.0043*** (15.69)
Demand Effect x Median Income ($\times$-10^3)	-0.0000 (-0.72)	-0.0000 (-0.48)
Evictions Up	-0.0160*** (-8.23)	-0.0161*** (-8.28)
Evictions Up x Bargaining Effect	-0.0031 (-0.50)	-0.0011 (-0.17)
Evictions Up x Demand Effect	-0.0015 (-0.25)	-0.0020 (-0.33)

	Ln(Sale Prices) All Investors	Ln(Sale Prices) Professional Investors
Ln(Time On Market)	-0.0296***	-0.0297***
	(-25.76)	(-25.83)
Ln(Listing Density)	0.0910***	0.0908***
	(65.04)	(64.88)
Annual Fixed Effects	Yes	Yes
Spatial Fixed Effects	Yes	Yes
Number of Observations	64,828	64,828
R^2	0.858	0.858

Notes: This table reports 3SLS regression models spanning the years 2019 to 2021 for Los Angeles County, with the natural logarithm of transaction prices as the dependent variable. The convention for the *Bargaining Effect* is Seller minus Buyer, while the *Demand Effect* is Seller plus Buyer. In the "All Investors" regression, the Seller (Buyer) indicators take value of 1 if the Seller (Buyer) is any type of investor (i.e., individual or professional). In the "Professional Investors" regression, the Seller (Buyer) indicators take value of 1 if the Seller (Buyer) is a professional investor. Due to the limited sample size of individual investors, those results are omitted. Regarding the race variables, a value of one is assigned if the racial composition within a particular census tract exceeds 50 percent. *Median Age* and *Median Income* correspond to the values associated with each traded home and its respective census tract. The *Evictions Up* indicator is set to one for month-over-month increases in evictions within the court district where a house sale occurs, and zero otherwise. The models include the additional housing characteristics noted in Tables 1 to 3. Spatial fixed effects are employed to control for over 300 municipalities. *T*-statistics are presented in parentheses, with *, **, and *** denoting *p*-values less than 0.10, 0.05, and 0.01, respectively.

Table 6: Bargaining and Demand Effects, with Demographic and Evictions Interactions

	Ln(Sale Prices) All Investors	Ln(Sale Prices) Professional Investors
Bargaining Effect	0.1480*** (4.64)	0.1230*** (3.72)
Demand Effect	-0.0595** (-1.97)	-0.0238 (-0.76)
Black	-0.0842*** (-8.27)	-0.0854*** (-8.42)
Latino	0.0467*** (10.37)	0.0479*** (10.67)
Other Nonwhite	-0.0816*** (-11.34)	-0.0817*** (-11.36)
Median Age	0.0000 (0.10)	0.0001 (0.23)
Higher Education	0.0124*** (115.15)	0.0124*** (115.66)
Bargaining Effect x Black	0.0827*** (3.19)	0.0740*** (2.74)
Bargaining Effect x Latino	0.0024 (0.17)	0.0001 (0.01)
Bargaining Effect x Other Nonwhite	-0.0567*** (-2.84)	-0.0640*** (-3.13)
Bargaining Effect x Median Age	-0.0019** (-2.42)	-0.0009 (-1.11)
Bargaining Effect x Higher Education	-0.0004 (-1.43)	-0.0007** (-2.36)
Demand Effect x Black	-0.0784*** (-2.90)	-0.0733*** (-2.62)
Demand Effect x Latino	0.0702*** (5.19)	0.0614*** (4.31)
Demand Effect x Other Nonwhite	-0.0485*** (-2.59)	-0.0469** (-2.42)
Demand Effect x Median Age	-0.0016** (-2.12)	-0.0025*** (-3.19)
Demand Effect x Higher Education	0.0047*** (17.01)	0.0048*** (16.49)
Evictions Up	0.0267* (1.80)	0.0290** (1.96)
Evictions Up x Bargaining Effect	0.0229 (0.47)	0.0632 (1.25)
Evictions Up x Black	0.0121 (0.82)	0.0134 (0.90)
Evictions Up x Bargaining Effect x Black	0.0409 (1.05)	0.0474 (1.19)
Evictions Up x Latino	-0.0018 (-0.30)	-0.0028 (-0.47)
Evictions Up x Bargaining Effect x Latino	-0.0099 (-0.46)	-0.0058 (-0.26)

	Ln(Sale Prices) All Investors	Ln(Sale Prices) Professional Investors
Evictions Up x Other Nonwhite	0.0311*** (3.93)	0.0315*** (4.00)
Evictions Up x Bargaining Effect x Other Nonwhite	0.0369 (1.24)	0.0463 (1.49)
Evictions Up x Median Age	-0.0007* (-1.75)	-0.0007* (-1.91)
Evictions Up x Bargaining Effect x Median Age	-0.0007 (-0.59)	-0.0020 (-1.61)
Evictions Up x Higher Education	-0.0005*** (-3.27)	-0.0005*** (-3.26)
Evictions Up x Bargaining Effect x Higher Education	0.0000 (0.05)	0.0003 (0.62)
Evictions Up x Demand Effect	-0.0697 (-1.52)	-0.111** (-2.33)
Evictions Up x Demand Effect x Black	0.0194 (0.48)	0.0090 (0.22)
Evictions Up x Demand Effect x Latino	-0.0331 (-1.59)	-0.0252 (-1.15)
Evictions Up x Demand Effect x Other Nonwhite	-0.0542* (-1.92)	-0.0638** (-2.16)
Evictions Up x Demand Effect x Median Age	0.0031*** (2.72)	0.0043*** (3.65)
Evictions Up x Demand Effect x Higher Education	-0.0010** (-2.38)	-0.0012*** (-2.68)
Ln(Time On Market)	-0.0279*** (-24.15)	-0.0280*** (-24.23)
Ln(Listing Density)	0.0835*** (59.39)	0.0834*** (59.26)
Annual Fixed Effects	Yes	Yes
Spatial Fixed Effects	Yes	Yes
Number of Observations	65,151	65,151
R^2	0.860	0.860

Notes: This table reports 3SLS regression models spanning the years 2019 to 2021 for Los Angeles County, with the natural logarithm of transaction prices as the dependent variable. The convention on the *Bargaining Effect* is Seller minus Buyer while the *Demand Effect* is Seller plus Buyer. In the "All Investors" regression, the Seller (Buyer) indicators take value of 1 if the Seller (Buyer) is any type of investor (i.e., individual or professional). In the "Professional Investors" regression, the Seller (Buyer) indicators take value of 1 if the Seller (Buyer) is a professional investor. Due to the limited sample size of individual investors, those results are omitted. The race variables take the value of 1 if the racial composition for a particular census tract is greater than 50 percent. *Higher Education* is a continuous variable representing the percentage of census tract residents with a college or advanced degree. *Median Age* and *Median Income* correspond to the tract-level values associated with each traded home, based on the census tract in which the property is located. *Evictions Up* is an indicator equal to 1 for month-over-month increases in evictions in the court-district where a house sale is located, and 0 otherwise. The models include the additional housing characteristics noted in Tables 1 to 3. Spatial fixed effects control for over 300 municipalities. *T*-statistics are in parentheses with *, **, and *** denoting *p*-values less than 0.10, 0.05, and 0.01, respectively.

Table 7: Bargaining and Demand Effects, including Income and Interactions

	Ln(Sale Prices) All Investors	Ln(Sale Prices) Professional Investors
Bargaining Effect	0.1000*** (3.05)	0.0755** (2.20)
Demand Effect	-0.0290 (-0.92)	0.0024 (0.07)
Black	-0.0820*** (-8.10)	-0.0830*** (-8.23)
Latino	0.0424*** (9.45)	0.0434*** (9.70)
Other Nonwhite	-0.0785*** (-10.93)	-0.0785*** (-10.93)
Median Age	-0.0003 (-1.11)	-0.0003 (-1.07)
Higher Education	0.0120*** (91.18)	0.0120*** (91.57)
Median Income ($\times$-10^3)	0.0016*** (2.85)	0.0017*** (2.88)
Bargaining Effect x Black	0.0789*** (3.06)	0.0731*** (2.73)
Bargaining Effect x Latino	0.0181 (1.28)	0.0167 (1.11)
Bargaining Effect x Other Nonwhite	-0.0622*** (-3.13)	-0.0686*** (-3.37)
Bargaining Effect x Median Age	-0.0006 (-0.73)	0.0004 (0.45)
Bargaining Effect x Higher Education	0.0005 (1.31)	0.0002 (0.58)
Bargaining Effect x Median Income ($\times$-10^3)	-0.0005*** (-3.08)	-0.0005*** (-3.18)
Demand Effect x Black	-0.0782*** (-2.91)	-0.0768*** (-2.77)
Demand Effect x Latino	0.0632*** (4.62)	0.0541*** (3.75)
Demand Effect x Other Nonwhite	-0.0485*** (-2.60)	-0.0482** (-2.50)
Demand Effect x Median Age	-0.0021*** (-2.63)	-0.0028*** (-3.40)
Demand Effect x Higher Education	0.0047*** (13.66)	0.0048*** (13.13)
Demand Effect x Median Income ($\times$-10^3)	-0.0001 (-0.59)	-0.0000 (-0.62)
Evictions Up	0.0250* (1.69)	0.0263* (1.79)
Evictions Up x Bargaining Effect	0.0485 (0.98)	0.0851* (1.65)
Evictions Up x Black	0.0125 (0.84)	0.0134 (0.91)

	Ln(Sale Prices) All Investors	Ln(Sale Prices) Professional Investors
Evictions Up x Bargaining Effect x Black	0.0418 (1.08)	0.0447 (1.13)
Evictions Up x Latino	-0.0022 (-0.37)	-0.0030 (-0.51)
Evictions Up x Bargaining Effect x Latino	-0.0215 (-1.00)	-0.0173 (-0.77)
Evictions Up x Other Nonwhite	0.0316*** (3.97)	0.0317*** (4.00)
Evictions Up x Bargaining Effect x Other Nonwhite	0.0396 (1.33)	0.0473 (1.53)
Evictions Up x Median Age	-0.0006 (-1.63)	-0.0006* (-1.69)
Evictions Up x Bargaining Effect x Median Age	-0.0015 (-1.14)	-0.0027** (-1.99)
Evictions Up x Higher Education	-0.0005*** (-2.84)	-0.0005*** (-2.73)
Evictions Up x Bargaining Effect x Higher Education	-0.0008 (-1.44)	-0.0005 (-0.87)
Evictions up x Median Income ($\times$-10^3)	0.0000 (0.17)	0.0000 (0.02)
Evictions up x Bargaining Effect x Median Income ($\times$-10^3)	0.0004* (1.84)	0.0004* (1.70)
Evictions Up x Demand Effect	-0.0888* (-1.87)	-0.122** (-2.47)
Evictions Up x Demand Effect x Black	0.0176 (0.44)	0.0118 (0.29)
Evictions Up x Demand Effect x Latino	-0.0279 (-1.33)	-0.0207 (-0.94)
Evictions Up x Demand Effect x Other Nonwhite	-0.0545* (-1.93)	-0.0616** (-2.08)
Evictions Up x Demand Effect x Median Age	0.0034*** (2.77)	0.0043*** (3.38)
Evictions Up x Demand Effect x Higher Education	-0.0009* (-1.71)	-0.0011** (-2.09)
Evictions Up x Demand Effect x Median Income ($\times$-10^3)	0.0000 (0.12)	0.0001 (0.45)
Ln(Time On Market)	-0.0296*** (-25.71)	-0.0297*** (-25.81)
Ln(Listing Density)	0.0906*** (64.80)	0.0905*** (64.67)
Annual Fixed Effects	Yes	Yes
Spatial Fixed Effects	Yes	Yes
Number of Observations	64,828	64,828
R^2	0.858	0.858

Notes: This table reports 3SLS regression models spanning the years 2019 to 2021 for Los Angeles County, with the natural logarithm of transaction prices as the dependent variable. The *Bargaining Effect* convention is Seller minus Buyer while the *Demand Effect* is Seller plus Buyer. In the "All Investors" regression, the Seller (Buyer) indicators take value of 1 if the Seller

(Buyer) is any type of investor (i.e., individual or professional). In the "Professional Investors" regression, the Seller (Buyer) indicators take value of 1 if the Seller (Buyer) is a professional investor. Due to the limited sample size of individual investors, those results are omitted. Regarding race variables, a value of one is assigned if the racial composition within a particular census tract exceeds 50 percent. *Median Age* and *Median Income* correspond to the values associated with each traded home and its respective census tract. *Higher Education* is a continuous variable representing the percentage of census tract residents with a college or advanced degree. The *Evictions Up* indicator is set to one for month-over-month increases in evictions within the court district where a house sale occurs, and zero otherwise. These models incorporate additional housing characteristics as noted in Tables 1 to 3. Spatial fixed effects are utilized to account for variation across over 300 municipalities. *T*-statistics are displayed in parentheses, with **, **, and *** indicating *p*-values less than 0.10, 0.05, and 0.01, respectively.