The Impact of Institutional Investors on Homeownership and Neighborhood Access*

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Abstract

Since 2012, institutional investors entered the single-family rental market in areas that subsequently experienced high rent and house price growth. This paper estimates a structural model where institutional landlords benefit from economies of scale and market power. Entry created a tradeoff: Renters benefited from lower rents because institutional investors expanded rental supply by 0.5 homes for each home purchased, but homeownership fell by 0.22 per purchase. In their top decile markets, entry explains 20% of the observed price increase. Supply responses dampened these effects. Overall, economies of scale, not market power, drive institutional investors' impact on the single-family rental market.

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1. Introduction

Historically in the US, large landlords operated multifamily rentals and single-family rentals were operated by small-scale "mom-and-pop" landlords. However, since 2012, institutional investors have entered the single-family rental market and purchased up to 8.5% of the housing stock in certain ZIP codes in the suburbs of some US cities, including Atlanta, Phoenix, and Tampa. The new institutional investor landlords differ from the existing "mom-and-pop" landlords: They have spatially concentrated portfolios of up to 85,000 rather than 1–3 homes. While the implications of these differences for the housing market are unclear, regions where institutional investors bought homes have experienced higher price and rent growth than the rest of the country.

These facts raise the question of whether institutional investors' entry into the single-family rental market has increased prices, increased rents, and lowered homeownership. Policymakers, concerned that the institutional investor demand shock has lowered homeownership and that institutional investors' market power has raised rents, have proposed bans on institutional investors in single-family homes[1] and a 5% annual rent increase limit for corporate landlords.[2] However, the implications of institutional investor entry for the housing market depend on large landlords' underlying incentives and the responses of others in the housing market. For example, the net effect of institutional investor entry on rents depends on whether their market power leads to a decrease in the rental supply or, instead, if they have low operating costs which could lead to an increase in the rental supply. In addition, numerous forces may offset some of the impact of institutional investor demand on prices and homeownership: The construction sector can build homes and small landlords can sell their homes. To quantify institutional investors' impact, it is important to accurately account for each mechanism to disentangle these forces.

This paper examines how institutional investor landlords differ from "mom-and-pop" landlords and quantifies the implications of these differences for the housing market. By estimating a structural model of the housing market with landlords that are heterogeneous in operating costs and market power, households, and construction, I find that institutional investor entry raised

[1] End Hedge Fund Control of American Homes Act, American Neighborhoods Protection Act.
[2] "White House calls on corporate landlords to cap rent increases at 5%."

local prices by less than the observed price increases in the markets where they entered and decreased the quantity of homes available for homeownership by 0.22 homes for each home purchased. Despite the presence of market power, I show that large landlords increased the rental supply by 0.5 homes for each home purchased and decreased rents on net due to low operating costs at scale. Policies seeking to ban institutional investors or cap annual rent increases would increase rents by reducing the rental supply—the opposite of their intended effect on the rental market. Overall, I find that institutional investor entry benefited renters by lowering rents and increasing the quantity of rentals in neighborhoods with few rentals, but made it harder for prospective homeowners to buy homes.

To understand the role institutional investors play in the market, it is important to know how they differ from existing "mom-and-pop" landlords. With small landlord cost data from the Rental Housing Finance Survey (RHFS) and large landlord cost data from earnings statements supplements for the public single-family rental real estate investment trusts (REITs), I show that the key difference is that institutional investor landlords operate at lower average costs and scale more efficiently than existing "mom-and-pop" landlords. All else held equal, the ability to operate large portfolios at low costs could lower rents due to increasing the rental supply. However, large portfolios could allow them to gain a large share of local rentals, which can give rise to market power, which could decrease the rental supply and push rents upwards.

Institutional investors also differ in the potential to use large portfolios to affect rents. I propose and support a novel channel of market power in real estate: Adjusting quantities through the number of units owned, rather than occupancy, to maximize profit. A stylized model shows that landlords prefer the units channel when the cost of adjusting the number of units is low relative to the cost of holding a vacant unit, and when the sold unit is likely to exit the rental market by going to an owner-occupier. Empirically, large landlords adjust their portfolio sizes in markets by up to 14.7% units in a year in a manner consistent with profit maximization, while high occupancy and low turnover appear unrelated to large mergers. The evidence is consistent with market power in single-family rentals expressed by landlords converting fewer owner-occupied homes to rentals to not dilute their own supply, rather than by buying existing rentals and holding some vacant. This is better for welfare because someone else can live in that unit or rent it out.

I develop a structural model designed to quantify the relative importance of these forces to assess the overall impact of institutional investors. The model incorporates differences in landlords' cost curves and market power in a setting where households, small landlords, and construction can respond to institutional investor entry.

Rental supply in the model is determined endogenously by the sum of large and small landlords' supplies, allowing for the possibility that large landlords crowd out small landlords. Small landlord supply is the aggregate of the decisions of individual landlords, who choose whether to operate a rental or not. Cross-sectional heterogeneity in costs leads to decreasing returns to scale. Large landlords with constant returns to scale choose a quantity of homes in each region to purchase and then supply as rentals to maximize profits, taking into account that their quantities will affect rents and prices and therefore behave as Cournot oligopolists. By endogenizing large landlord demand, I can simulate counterfactuals which affect their portfolio sizes including mergers, rent-stabilization, and shutting down construction. Both landlord types have the same expectations about each region's rent growth based on past population growth and other trends, which allows large landlords to select regions with high expected rent growth.

To quantify the impact of institutional investors on homeownership, and assess the impact on which neighborhoods renters can access, the model incorporates rich substitution patterns for households. Households choose where to live and whether to own, rent single-family, or rent multifamily by solving a discrete-choice problem. I estimate the discrete choice parameters with methods from Berry, Levinsohn and Pakes (1995) and Conlon and Gortmaker (2020) and data from the Census American Community Survey (ACS). To get accurate geographic and tenure choice substitution, moving costs are estimated with bilateral migration data from Verisk (formerly Infutor). To get distributional effects, I estimate demand for different income groups of households. Elasticities for prices and rents are identified with an instrumental variables (IV) strategy.

To allow supply responses to potentially dampen the effects of demand shocks on prices and homeownership, the model includes an aggregate builder that increases the quantity of homes when prices increase. The builder uses new unit supply elasticities from Baum-Snow and Han (2024), which allow for a heterogeneous construction response in each region of the model.

With the estimated model, I simulate the entry of 3 identical institutional investors who enter the housing market in 2012 and choose locations and quantities of single-family homes to buy and supply as rentals. I recover prices, rents, and quantities for Georgia, the epicenter of large landlord entry into the single-family rental market.

The model shows that institutional investor entry decreased the number of homes available for owner occupancy by 0.22 for each home purchased, which is five times smaller than a back-of-the-envelope calculation that doesn't include supply responses. When institutional investors buy a home and supply it as a rental, higher demand for owning homes increases prices, and the increased supply of rentals decreases rents. This causes builders to build 0.28 homes and small landlords to sell 0.5 homes. Institutional investors increased the number of rentals by 0.5 for each home they purchased, which is less than 1:1 because they crowded out small landlords. Evidence in the observational data supports that these margins of adjustment are relevant: Where institutional investors entered the market, small landlords exited, builders built homes, and the rental supply increased. The model shows that low-income renters moved into the rentals supplied by the institutional investors—which aligns with data showing that renters from lower-income areas with worse historic economic opportunities moved into the investors' rental homes—and therefore that the institutional investors increased neighborhood access for low-income renters.

I find that institutional investors raised prices and lowered rents in their most concentrated regions, but both effects are far below observed correlations with price and rent increases. The price impact was significantly dampened by supply responses: It is 2.5 times as large in a counterfactual where the construction response is shut down. Institutional investors decreased rents because they increased the supply of single-family rentals. To reverse the results, for institutional investors to increase rents, they must crowd out more small landlord supply than they add. I use a stylized model to show that a necessary condition for this is that large landlords must raise small landlord costs, otherwise small landlords would be happy to supply the initial number of units at initial rents. The estimated model parameters are far from those required to reverse the results in the rental market: Twice as many small landlords would need to be crowded out.

The difference between the model-implied and the observed increases in prices and rents are consistent with institutional investors having targeted regions with expected rent and price growth to maximize returns. INVH in its initial public offering (IPO) filings described how it chose markets with expected population, employment growth, and constrained new supply, to target rent and price growth. Consistent with this, areas where institutional investors purchased homes experienced large subsequent increases in population relative to the rest of the country. The model includes the incentives of large landlords to target regions with expected rent growth and supports that targeting drove the association between institutional investors and rent growth.

To validate the model's measurement of the effect of market power on rents, I simulate a merger between 2 of 4 large landlords and find similar rent impacts to those in Gurun, Wu, Xiao and Xiao (2022), which uses quasi-experimental evidence from mergers to examine the effect of concentration on rents. Because market power in single-family rentals is exercised through changing units (Cournot), and not increasing vacancy (Bertrand), mergers release homes back into the market and therefore lower housing prices and increase homeownership.

I simulate two proposed policies. An effective ban of large single-family landlords decreases home prices, increases rents, and small landlords gain a large share of the homes that institutional investors are forced to sell. A 5% cap on annual rent increases for large landlords decreases the quantity of rentals that large landlords supply and increases rents. The results show that not accounting for the fact that institutional investors increase the quantity of rentals leads to policies having the opposite of their intended effects on rents.

This paper does not include a number of mechanisms that are also operative in multifamily and across landlord types including evictions (Raymond, Duckworth, Miller, Lucas and Pokharel, 2018), renovations (Lee and Wylie, 2024), and deceptive fees[3]. This paper also abstracts away from the effects of institutional investors on neighborhood amenities (Gurun et al., 2022; Billings and Soliman, 2024). I focus on mechanisms unique to the single-family rental market that are key for policymakers who propose bans and rent increase caps: The potential for institutional investors to crowd out homeowners, and raise rents through market power.

This paper contributes to the literature on institutional investor impact on housing markets which has lacked consensus. Mills, Molloy and Zarutskie (2019) and Gould Ellen and Goodman (2023) describe characteristics of institutional investor entry. A number of papers study the entry of out-of-town buyers and small investors into housing markets including Chinco and Mayer (2015), Favilukis and Van Nieuwerburgh (2021), Gorback and Keys (2025), and Garriga, Gete and

[3] Federal Trade Commission fined Invitation Homes in 2024.

Tsouderou (2023). Several papers study the impact of institutional investors on prices and rents with reduced form methods using variation based on random assignment (Ganduri, Xiao and Xiao, 2022; Lambie-Hanson, Li and Slonkosky, 2022), bans of investors (Francke, Hans, Korevaar and van Bekkum, 2023), mergers (Gurun et al., 2022; Austin, 2022), instrumental variables (Gorback, Qian and Zhu, 2024; Hanson, 2024), and absorbing geographic variation (Lee and Wylie, 2024; An, 2023; Giacoletti, Heimer, Li and Yu, 2024). Results on prices and rents differ because different identification strategies isolate different channels through which investors affect the market.

My research makes four novel contributions to this literature. First, this paper provides a framework through which to interpret differing results from the literature by developing a structural model which includes many forces jointly. The framework makes it clear that what matters for the rental market impact is whether institutional investors increase or decrease the rental supply. This depends on the relative size of how many units they add due to low operating costs, limit due to market power, and decrease in equilibrium by crowding out small landlords. By modeling these forces jointly, I show that the operating cost channel dominates, that institutional investors would have to crowd out twice as many landlords to reverse the results, and that if policymakers only considered the market power channel, they would get the directional impact of institutional investors on rents wrong and enact counterproductive policy. This differs from existing work by Gurun et al. (2022) which studies mergers of institutional investors in single-family rentals because I can estimate the net effect of institutional investor entry on rents, incorporating both market power and lower operating costs.

Second, by endogenizing large landlord demand, the model allows for counterfactual simulations including two proposed policies and shutting down construction. Third, the model allows for the quantification of the homeownership impact of institutional investors because it accounts for the responses of builders and the crowding out of small landlords, both of which ease pressure on homeownership. The model accounts for those who move to become homeowners elsewhere, which is not included in local estimates of the homeownership impact. Fourth, I provide a novel analysis of heterogeneity in single-family landlord costs which is used to endogenize the decisions of heterogeneous landlords in the structural model.

Two contemporaneous papers, Barbieri and Dobbels (2025) and Chang (2025), also use structural models to study institutional investor impact on prices and rents. My paper contributes by modeling a number of forces jointly, including the quantity and location choices of institutional investors with market power and economies of scale, the endogenous quantity response of the small landlord sector, the response of households, and the response of the construction sector.

This paper also contributes to the literature on market power in rental housing. Calder-Wang and Kim (2024) study how algorithmic pricing can lead to market power in multifamily rentals. Watson and Ziv (2024) study market power in multifamily rentals in New York City. Barbieri and Dobbels (2025) study institutional single-family rental landlords' market power that comes from landlords' internalizing demand spillovers onto other units they own to raise rent and lower occupancy. I provide evidence for a new channel of market power in single-family rentals: Institutional investors maximize profits by adjusting their number of units, rather than occupancy. I use a stylized model to illustrate the economic forces that govern when a landlord would choose the units channel over the vacancy channel. Consistent with this, I model institutional investors as Cournot oligopolists who limit the number of units they own to not dilute their own product, where market power comes from their cost advantage relative to small landlords.

I contribute to the literature on how institutional investors affect neighborhood composition. Francke et al. (2023) shows how institutional investors increased neighborhood diversity in the Netherlands. Chang (2025) studies how large landlords increased the supply of rentals in the suburbs and therefore diversified them. This paper shows with individual level migration data that those who move into these rentals came from areas with worse historic economic opportunities.

2. Data

Property-Level Data. I use property-level data from the Verisk property files to identify institutional investor–owned homes for the descriptive analysis. The dataset consists of 150 million rows at the tax-lot level for the US for each cross-section of the data from February 2021 and each year from November 2015 to 2019. Each row contains information on property characteristics, mortgages, the anonymized owner mailing addresses, and the most recent sale. Full details on the construction of this dataset are in Appendix C. Filters including the exclusion of duplicates and non-residential properties result in a dataset of 110 million residential units. Unit counts are highly correlated with ZIP code–level housing unit counts in the Census ACS 5-year tables for 2020, as shown in Appendix Table A1. Rental units are under-counted by approximately 8% due to limitations counting the number of units in multifamily properties. I use the mortgage fields to study the financing for existing single-family rentals for small landlords and to create an empirical mortgage distribution for small landlords in each region of the model. Geographically granular housing completions are recovered by examining the year built information of each property, which in aggregate aligns with aggregate single-family completions in the Federal Reserve Economic Data, as shown in Appendix Figure A1. I observe the number of foreclosures from 2007 to 2011 at different geographic levels from Zillow ZTRAX.

I identify institutional investors' properties with the mailing addresses to which property tax forms are sent for each property, following Ganduri et al. (2022). I examine mailing addresses that correspond to the most single-family rental properties in the US, and manually identify the companies that correspond to these addresses. I focus on the 7 companies that owned the most single-family rentals as of 2021: Invitation Homes, American Homes for Rent, Tricon Residential, Progress Residential, Main Street Renewal, FirstKey Homes, and Home Partners of America. For these 7 companies, I can identify 235,057 properties in February 2021. For the companies that were publicly traded as of 2021 (Invitation Homes, American Homes for Rent, and Tricon Residential), I can identify 86–91% of their property quantities listed in Securities and Exchange Commission (SEC) filings, as shown in Appendix Table A2.

Landlord-Specific Operating Data. Small landlord operating costs and additional financing information come from the RHFS from the US Census. The survey samples housing units from the American Housing Survey to obtain a representative sample of landlords in the US and collects data on rents and components of costs. The dataset contains information on how many units are in each building and whether the owner is an individual or a corporation, but does not provide information on how many properties an owner owns, and is not longitudinal. The survey was conducted in 2015, 2018, and 2021. Desmond and Wilmers (2019) use these data to study multifamily housing costs. I create a dataset of small landlord single-family rental costs with the 2018 and the 2021 RHFS, which cover 2017 and 2020, respectively. The survey contains approximately 500 entries each year for 1-unit properties with the ownership category listed as "individual," which excludes corporations, REITs, and limited-liability companies (LLCs). I provide more details on the construction of this dataset for analysis in Appendix C. For the descriptive analysis, I use small landlord property tax and mortgage data from the RHFS. For the model calibration, I use region-specific property taxes and mortgage balance distributions from Verisk.

Large landlords' market-level cost components, revenue, occupancy, portfolio sizes, and company-level turnover come from earnings statement supplements for two public single-family rental REITs: INVH and AMH. These became public companies in February 2017 and August 2013, respectively. To examine operating costs, I look at same-store costs to exclude homes recently purchased or in the process of being sold. For the cost component analysis, I construct the market-level same-store adjusted funds from operations (AFFO) as a fraction of revenues. AFFO is a profitability measure common to REITs that focuses on cash flows because REITs have large depreciation expenses even though their properties will likely appreciate in value over time.

Individual-Level Migration Data. To analyze the differences between residents who move into institutional investor homes and those who move into other homes in the same census tract, I use the Verisk location history data. Verisk provides the last 10 locations for over 100 million individuals. Each location has an address ID, which can be linked to the property dataset to see if an individual moved into an institutional investor home, and what type of home they moved into. I describe the steps for cleaning this data to construct migration datasets in Appendix C. Appendix Table A3 shows this migration dataset is highly correlated with moves to and from a given ZIP code in the United States Postal Service (USPS) change-of-address data, and Appendix Table A4 shows the migration dataset is correlated with county to county flows in the ACS data.

Household Housing Quantities and Amenities Data. To estimate household demand for housing, I create a dataset of housing holdings using data from the census Public Use Microdata Sample (PUMS), which is a survey of approximately 1% of the US population each year. For each household, I observe the PUMA (census public-use microdata area) of residence, household income, and whether the household lives in an owner-occupied, single-family rental, or multifamily rental unit. PUMAs are census geographies with approximately 100,000–200,000 people. They are the most granular geographic unit for which the Census publicly releases yearly data rather than 5-year pooled samples. Any smaller geographic unit would require the use of tables created from 5-year averages, which would make it difficult to measure changes in prices and rents over a 9-year period, especially the years after the large price swing resulting from the Great Recession.

I aggregate these data to the PUMA, year, and household income group levels to obtain a panel of holdings data for income groups across the US from 2012 to 2019. The household income groups are 0–25k, 25–50k, 50–75k, 75–100k, and 100k+. The PUMA-level census tables include characteristics involved in the demand estimation relating to the housing stock, commute distance, and schools. Other characteristics include weather data for amenities from the US Department of Agriculture, topography data from Lutz and Sand (2022) that describe the fraction of a ZIP code area unavailable for building due to the presence of water, wetlands, or slopes, distance to the nearest city, distance to the nearest top-30 city, distance to the nearest coastline, and finally middle-school math test scores 2013 from Opportunity Insights. I describe the process to convert data across different geography types in Appendix C.

3. Descriptive Facts

3.1 Institutional Investor Activity

To understand which forces govern the impact of institutional investors on the housing market and build those into a structural model, we first need to know where institutional investors are relevant and why they chose those locations.

Institutional investors purchased concentrated portfolios of single-family homes in the suburbs of US cities. Appendix Figure B1 shows that institutional investors' largest markets are Sunbelt cities including Atlanta, Phoenix, and Tampa. While they owned only 0.17% of the housing stock in the US as of February 2021, they are spatially concentrated: In Paulding County, Georgia, which is in the Atlanta metro area, 7 institutional investors purchased 5.4% of all the housing stock from 2012 – 2021. Figure 1 Panel A shows census tract concentration of the 7 institutional investors studied. In a census tract in Rutherford County, Tennessee, between Nashville and Murfreesboro, these companies own 19% of the entire housing stock: 534 of the 2803 properties in the tract. In some tracts, the 7 companies combined own 77% of the total rental supply. Figure 1 Panel B shows the census tract concentrations of housing stock ownership for institutional investors in Atlanta, and displays the characteristic pattern that these investors buy homes in rings around the city. The high local concentration and low national share suggest that institutional investors are more likely to have had a local impact on US cities rather than a broad impact on the entire country.

They chose cities with low price-to-rent ratios and many foreclosures during the Great Recession. Results from a descriptive regression of institutional investor presence on local characteristics in Table B1 show that institutional investors own properties in PUMAs with low price-to-rent ratios, which is consistent with the business strategy of buying properties to hold and rent, and high population and job growth pre-trends, which is consistent with the targeting of expected price and rent appreciation. This strategy is confirmed in INVH's and AMH's IPO filings: INVH "selected markets that we believe will experience strong population, household formation and employment growth and exhibit constrained levels of new home construction. As a result, we believe our markets have and will continue to outperform the broader U.S. housing and rental market in rent growth and home price appreciation."[4] Institutional investors purchased homes in regions with many foreclosures during the Great Recession, which allowed them to get low acquisition costs and high expected price appreciation. This is confirmed in AMH's IPO filings: "We select our markets based on steady population growth, strong rental demand and a high level of distressed sales of homes that can be acquired below replacement cost, providing for attractive potential yields and capital appreciation."[5] Because price and rent appreciation are central to the business strategy of institutional investors, any analysis of their impact on prices and rents must separate causal impacts from their targeting incentives, and a model of investor location choice must include these targeting motives.

Regions with high concentrations of institutional investors experienced high subsequent growth in house prices, rents, and population. Figure B2 Panel A shows a binscatter of the association between institutional investors' share of a PUMA's total housing stock in 2019 and changes in housing prices and rents from 2012 to 2019, relative to the changes in the rest of the country. Institutional investor presence is associated with price increases of up to 40% more and rent increases

[4] INVH form S-11, page 4.
[5] AMH form S-11, page 7.

of up to 10% more than in the rest of the US from 2012 to 2019. High subsequent rent and house price growth highlight why institutional investors have received national attention from the media and politicians who have proposed banning institutional investors from owning and operating single-family rentals. Panel C shows the association of institutional investor entry with household growth from 2012 to 2019. Institutional investors chose areas that experienced large subsequent growth in population relative to the rest of the country. The differential growth in population suggests that factors other than institutional investor entry could have caused prices to rise.

In addition to possible price and rent impacts, institutional investors may have decreased homeownership if they converted owner-occupied homes to rentals, which would also expand the rental supply. Alternatively, institutional investors could have replaced other landlords or absorbed new construction. Property assessment data that includes the most recent purchase of each property allows me to examine approximately 17,000 purchases by institutional investors. In this subsample, institutional investors purchased 44% of their homes from owner occupants and 56% from non-owner occupants, which is consistent with results from Gorback et al. (2024). While these direct purchases are not equilibrium substitution patterns, they highlight that a model must consider that institutional investors may do a combination of turning owner-occupied homes to rentals, which would lower homeownership, and buying from other landlords, which would not. Figure B2 Panel D shows that institutional investors purchased homes in regions that experienced large subsequent construction growth relative to the rest of the country. Additionally, households could have moved to become homeowners elsewhere, suggesting a model with geographic substitution is needed to analyze the global homeownership impact. The stylized facts suggest that to analyze the homeownership impact of institutional investors, one needs to model the substitution patterns of households and small landlords, and the behavior of the construction sector.

If institutional investors increased the rental supply in areas with few rentals, it's possible they increased access to these neighborhoods for those who couldn't afford to buy a home. With individual-level migration data that shows where those who moved into institutional investor homes came from, I compare mean differences in origin and destination tract level characteristics from Opportunity insights that include median incomes, middle-school math test scores, and historic economic mobility data. Table 1 shows that those who moved into institutional investor homes came from areas with 12.2% lower median household incomes, 5.8% worse middle-school math test scores, a 6% higher likelihood of incarceration, and a 3.4% lower likelihood of a resident to enter the top income quintile. To the extent that the institutional investors increased rental supply, they did so in areas with better schools and economic mobility than the origin locations of the renters who moved into those investors' units. To isolate whether institutional investors' market presence not only increased the quantity of rentals in good locations but also changed the flow of people to those locations, I compare the renters who moved into institutional investor homes with those who moved into other homes in the same census tract. For the subsample of all movers into census tracts with institutional investor homes, I regress origin census tract characteristics on an indicator variable for moving into an institutional investor home for the first time, with destination census tract fixed effects. The results in Table 2 show that those who moved into institutional investor homes came from areas with populations who had lower incomes, fewer college degrees, and worse historic economic opportunities than those who moved into other homes in the same census tract, suggesting that institutional investor entry increased access to neighborhoods for people coming from these areas.

3.2 Landlord Heterogeneity and Quantity Choices

The previous section highlighted the importance of the substitution patterns of small landlords in determining the impact of large landlord entry. This section establishes facts about small and large landlord behavior that are key to the structural model.

The majority of single-family rentals are owned by tiny, local operators called "mom-and-pop" landlords. I construct operator-level single-family rental portfolios from the Verisk property data in February 2021. Figure 2 Panel A shows that 71% of single-family rentals are owned by operators with 1–3 properties and 75% by operators who do not operate in multiple counties. Institutional investors, some of which own over 80,000 units, are much larger than the majority of operators in this extremely fragmented market. Landlords with portfolios of 1000+ units, even in 2021, own only 1.8% of single-family rentals.

Small landlords minimize cash costs in a way that does not scale, suggesting that they have decreasing returns to scale. 63% of small landlords do not have a mortgage. Figure B4 Panels A and B show that small landlords who purchased homes recently are more likely to have a mortgage using data from the RHFS and Verisk. Panel C shows they have higher mortgage balances when they purchased recently. Additionally, Fannie Mae's mortgage underwriting liquid reserve requirements increase for additional investment properties up to 10, so financing constraints increase with the number of properties in the size range relevant to the majority of single-family rental operators.[6] The evidence shows that small landlords who recently increased portfolio sizes have higher cash costs through interest expenses than if they did not grow. Figure 3 Panel A shows these dynamics in the cross section with a histogram of small landlords, sorted by cash costs as a fraction of rent. The graph also shows the fraction of each histogram bucket with a mortgage. High-cost small landlords are more likely to have a mortgage than low-cost small landlords. 83% of small landlords do not use professional managers. An additional property likely raises property management expenses on average, due to the move from not having a manager to hiring one due to time constraints. On average, a property manager costs 10% of rent in the RHFS data.

For the baseline analysis of the impact of large landlord entry, it is not necessary to model large landlord supply because I could simulate the responses of others in the housing market to the observed quantity and location choices of large landlords. However, for counterfactuals where large landlord quantities adjust including mergers, regulation, and the shutting down of the construction sector, we need to understand large landlord supply curves in the region of quantities relevant to the counterfactuals.

Large landlords have lower average operating costs than small landlords. I plot INVH and AMH's average operating costs against the small landlord average and show they are significantly lower in Figure 2 Panel B. It's not necessary for the model in this paper to show that large landlords pay less to operate the same properties; accurate operating costs in the relevant quantity regions are sufficient. However, observational data, anecdotes, and other studies suggest that large landlords have operating advantages that drive the results from Figure 2 Panel B. The figure shows that large landlords have lower property tax expenses, and Austin (2022) documents how large landlords systematically appeal property tax assessments to lower payments. Large landlords pay 1-2% of their rent in insurance rather than 5-6% that small landlords pay. Operators say this is due to bargaining with insurers for bulk discounts. Kim, Mahajan and Wang (2025) uses CMBS data with insurance costs to show that larger operators pay less in insurance. Appendix A offers additional descriptive analysis about cost differences between small and large landlords

[6] Fannie Mae minimum reserve requirements.

including bargaining for materials, additional sources of capital, and the possibility that vertical integration lowers costs.

Large landlords have constant returns to scale in operating costs over a large range of relevant quantities for counterfactuals. Figure B5 shows there is no association between INVH's market-level average operating expenses per home and the market average portfolio size. I examine the effect of INVH's purchase of Starwood Waypoint Homes (SWH) in 2017, where its portfolio size rose from approximately 50,000 to 82,000 homes, on operating expenses per home. In Figure 3 Panel B, I plot the change in operating expenses per home against the change in number of homes from this merger for each market. While this variation is not exogenous because they may choose to expand in areas where they expect operating expenses to decrease for other reasons, the figure suggests that INVH can almost double the number of homes that it has in a market without raising its operating costs per home. Most likely, the companies experienced increasing returns to scale early on as they paid fixed costs to build capabilities for management, acquisition, and renovation, and then, in later stages, their returns to scale became constant, and would eventually decrease if they grew large enough. The variation I am able to observe suggests that the assumption of constant returns to scale in operating costs is reasonable for the number of homes in the range around the merger quantities—the relevant region for model simulations.

Finally, large landlords adjust quantities of units, rather than occupancy, to maximize profits. I examine occupancy of INVH at the market level in Figure 4 Panel A and company-level turnover in Panel B (INVH does not provide market-level turnover). Occupancy did not change around the date of INVH's merger with SWH, and instead follows broad trends such as the move of people to the suburbs following COVID-19. Quarterly turnover does not appear to change due to the merger and instead follows a consistent downward trend. High occupancy rates and low turnover that move due to trends unrelated to a large merger suggest that the mechanism through which market power is expressed is not increasing vacancies or turnover to raise rents.

Institutional investors make large portfolio adjustments consistent with profit maximization. Figure 5 Panel A shows INVH's market-level cumulative organic growth in each quarter following the merger with SWH. Changes in the number of units are at larger magnitudes than occupancy changes at the market level. In a number of markets, INVH decreased the quantity of homes owned after the merger by up to 7.5%. In Seattle, INVH increased its portfolio size organically by 25%. Panel B shows the relationship between the cumulative net organic growth and net operating income margins in each market in the year after INVH's merger with SWH. INVH adds homes organically in markets where operating margins are high, and decreases homes in markets where operating margins are low. The adjustment in number of units based on net operating margins is consistent with profit maximization, therefore suggesting that changes in units may be the strategic variable of choice for institutional investors.

The evidence motivates my modeling large landlords as Cournot oligopolists, who adjust quantities through units to maximize profits, rather than Bertrand oligopolists, who set rents and then vacancy adjusts. A stylized model in Appendix B shows that large landlords would maximize profits by adjusting units when vacancy costs are higher than adjustment costs, as is likely in single-family rentals, and by occupancy when adjustment costs are higher as is more likely in multifamily. Other studies in multifamily analyze vacancy, including Calder-Wang and Kim (2024) and Watson and Ziv (2024), and Barbieri and Dobbels (2025) analyzes vacancy in single-family.

While the evidence of using quantities to maximize profits is consistent with Cournot oligopoly and not Bertrand, it is not causal evidence of large landlords' setting quantities to internalize their market impacts. An alternative explanation consistent with the evidence is profit maximization through quantities in the presence of capital constraints. However, Cournot oligopoly is sufficient to model this behavior in equilibrium as well. Consider a rental company that can own only \$10 billion of assets, that reallocates its assets across regions each period based on expected price and rent appreciation. Given the assumption that its quantities are large enough to move prices and rents, adjustments in period 1 change prices and rents and therefore expected price and rent appreciation. Period 2 adjustments based on the new expected appreciation internalize the company's own past impacts on prices and rents.

4. Stylized Model of One Region

I incorporate the descriptive facts into a stylized, one region model of the single-family housing market to illustrate the economic channels through which institutional investor entry can affect the housing market, and connect parameters to result magnitudes and directions.

Figure 6 Panel A shows the supply and demand curves for single-family rentals in one region. I assume that aggregate rental demand is downward sloping. Based on the empirical evidence in the previous section, I assume that the aggregate small landlord has decreasing returns to scale and therefore upward sloping supply. While large landlords in this example have constant returns to scale, consistent with the evidence that they have constant operating costs per unit over a large range of quantities, the economic takeaways from this section do not depend on this assumption and would still hold if large landlords had upward sloping supply. Large landlords have marginal costs below market rents, which is consistent with empirical data of their cash margins in each market and reasonable assumptions about opportunity cost of capital. If the large landlords enter the market and choose competitive quantities, the equilibrium moves to the right from A to B: Rent decreases and the number of rentals increases.

Figure 6 Panel B shows supply and demand for single-family rentals modeled as a Cournot oligopoly. Small landlords are price takers and large landlords choose quantities to maximize profits by adjusting units owned, based on the empirical evidence in the previous section that large landlords adjust their number of units owned consistent with profit maximization. In this example, I assume that there is only one large landlord. This landlord can supply a significant amount of demand that small landlords cannot, due to lower costs, and therefore is a monopolist over the residual demand. A profit-maximizing large landlord therefore can internalize the impact that its quantity choice has on rent, and choose the profit maximizing quantity at which the residual marginal revenue intersects its cost curve. This market power shifts the equilibrium left to C: Rents increase and quantities decrease compared to B.

While Panel B shows a decrease in rents, institutional investor entry could increase rents if entry raises small landlord costs by enough that small landlords sell more rentals than large landlords add, and therefore decrease the rental supply:

$$\Delta Q = \Delta Q_{small} + \Delta Q_{large}. \tag{1}$$

Institutional investor entry can raise small landlord costs by increasing property values, which would then increase components of costs that depend on property values including property taxes, insurance, and the opportunity cost of owning property. Figure 6 Panel C shows how the increased demand for owning homes caused by institutional investor demand raises house prices when supply of homes from other homeowners and builders is inelastic. Panel D shows how increased home prices shift small landlord supply to the left. If large landlords were to raise rents by crowding out more small landlord supply than large landlords add, this would be represented by a shift in small landlord supply to the left far enough that C would be to the left of A.

Functional form assumptions in this simple setting allow us to connect the direction of the rent impact with supply and demand parameters. For this stylized model, I assume demand for renting is linear and downward sloping, that the aggregate small landlord has linear and upward sloping supply, where marginal costs also depend on home prices, and that the purchase price of a home changes when large landlords buy homes due to the inelastic supply of homes to own by others in the market and builders, where prices move with some multiplier M:

$$Rent = a - b(Q_{small} + Q_{large}), \tag{2}$$

$$MC_{small} = c + d \times Q_{small} + e \times Price, \tag{3}$$

$$\Delta Price = M \times Q_{large}. \tag{4}$$

Small landlords are price takers, so the equilibrium condition sets rents equal to marginal costs:

$$a - b(Q^*_{small} + Q_{large}) = c + d \times Q^*_{small} + e \times Price. \tag{5}$$

Solving for the change in small landlord quantity given a change in large landlord quantity from 0 to Q_{large} results in a per unit relationship for small landlord adjustments given large landlord entry:

$$\Delta Q^*_{small} = -\left(\frac{b + e \times M}{b + d}\right) Q_{large} \tag{6}$$

The fraction can be thought of as a "crowd out ratio." If it's greater than 1, small landlord quantities decrease by more than large landlords add to the rental supply, decreasing the rental supply and raising rents. If less than 1, large landlord entry increases quantities and lowers rents. A necessary but not sufficient condition for large landlord entry to raise rents is that entry must raise small landlord costs ($e \times M$ must be greater than 0), otherwise small landlords would be happy to supply the original quantity at original rents. While in this setting large landlords can affect small landlord costs only through changing property values, other channels that affect small landlord costs can play the same role as $e \times M$. For example, if large landlords additionally provide property management services for small landlords at greater value than existing offerings, this could lower small landlord costs and therefore the crowd out ratio. This is possible, given that Invitation Homes offers property management services to homes it does not own (17,261 homes as of June 30th, 2024). Alternatively, if large landlords were able to change regulations to make it more difficult for others to operate or build, this would increase the crowd out ratio.

In this setting, multiple operators can supply the same product. By having one rental good within-PUMA within-single-family, the model can first allow for a Cournot specification that aligns with the empirical observations that institutional investors adjust property counts to maximize profits, second match the fact that institutional investors often buy homes directly from small landlords, and therefore often supply the same good, and third map net quantity changes of large landlords, small landlords, and builders to rent changes. The data support the common demand assumption given that I observe that large landlords buy 56% of their properties from small landlords. I compare characteristics of small landlord and large landlord rentals in ZIP codes where more than 95% of the rental stock is single-family in Table B2 and show that the rental stock is substantially more similar in bedrooms, bathrooms, and year built when limiting to within single-family within ZIP comparisons than when allowing for comparison across property types in Table B3. Differentiated demand within-PUMA within-single-family would lower the impact of institutional investors on small landlord rents.

The supply block does not require that I identify exact cost differences for landlord types in supplying the same unit. It requires accurate small landlord supply curves within each PUMA and for counterfactuals that are not the baseline, it requires that I accurately model large landlord supply curves within the relevant quantities for the counterfactual. Selection into lower cost properties by large landlords does not invalidate the supply block, provided I accurately measure each supplier's costs. Institutional investors could, in theory, enter by purchasing only owner-occupied units that happen to be cheaper to operate, lower rents and raise costs for small landlords, and therefore affect small landlord quantities and common rental demand.

5. Quantitative Model with Multiple Regions

The main model includes multiple PUMA-level regions with integrated ownership, single-family, and multifamily rental markets. The key innovation is the supply side with endogenous small landlords who are price takers and have decreasing returns to scale in aggregate, endogenous large landlords who choose locations and quantities, internalizing their impact on the market, and a construction sector that builds homes when prices increase.

By construction, it excludes unmodeled forces, which helps isolate the impact of institutional investor entry from increases in population that institutional investors may have predicted. However, it also excludes other possible mechanisms for investor impact such as renovations (Lee and Wylie, 2024). If institutional investors renovate properties, this could increase demand for these properties and therefore increase rents, but it's not clear that this is negative for renters in contrast to market power induced decreases in quantities with no change in quality. There is varied evidence from Gurun et al. (2022) and Billings and Soliman (2024) on the effect of institutional investors on neighborhood crime. While changes to neighborhoods are important for households, this paper focuses on identifying and quantifying the homeownership impact of institutional investor entry, comparing whether low operating costs or market power drive the main rental market impacts for investors, and identifying market-level price and rent impacts.

5.1 Housing Demand

A household from origin location i in income group h in asset class l (owner-occupied housing, single-family rental, or multifamily rental), solves a discrete-choice problem to determine where to move, j, and which asset class k to live in at the destination. The model is similar to those in McFadden (1978), Bayer, Ferreira and McMillan (2007), and Diamond (2016) for housing, and Koijen and Yogo (2019), Koijen and Yogo (2019b), Koijen, Richmond and Yogo (2023), and Jiang, Richmond and Zhang (2024) for financial markets. Income heterogeneity allows for heterogeneity in price and rent elasticities and distributional impacts. Origin location and asset class heterogeneity allow for realistic spatial and asset class substitution patterns. Not moving is represented by $j = i$ and $k = l$.

Households maximize utility based on characteristics of the destination location and asset class, $X_{j,k}$, and a utility cost of moving from location i asset class l to location j asset class k: $\tau_{(i,l)\to(j,k)}$. Each asset has a log price of $p_{j,k}$, which is the log of the purchase price, single-family rent, or multifamily rent. A region asset class has unobservable quality $\xi_{h,j,k}$, and households have a latent demand denoted by $\varepsilon_{h,(i,l)\to(j,k)}$. Indirect utility for moving from (i,l) to (j,k) is therefore:

$$u_{h,(i,l)\to(j,k)} = \beta_{h,k,0}p_{j,k} + \beta_{h,k,d}X_{j,k} + \tau_{(i,l)\to(j,k)} + \xi_{h,j,k} + \varepsilon_{h,(i,l)\to(j,k)}. \tag{7}$$

The fraction of households of a given income type in a region and in an asset class, $w_{h,j,k}$, is determined by the sum of movers to the region and asset class. The share sums to 1 for each group h. With type 1 extreme value errors, this is:

$$w_{h,j,k} = \sum_{i,l} \frac{\exp(u_{h,(i,l)\to(j,k)})}{1+\sum_{(m,s)}\exp(u_{h,(i,l)\to(m,s)})} w_{h,i,l}. \tag{8}$$

$X_{j,k}$ includes characteristics related to climate (January temperature, January sunlight, July temperature, July humidity), the physical housing stock (median year built, median number of rooms, median fraction of the PUMA that is single-family housing), amenities and schools (fraction of the population with a commute under 45 minutes, log distance to nearest MSA, log distance to nearest top-30 MSA, fraction of the high-school-aged population in high school, fraction of the high-school-aged population in private school), and topography (average amount of land within 3 miles unavailable for construction because of water, wetlands, and total unavailable land), along with year fixed effects. A dummy variable for whether the destination asset class is owner-occupied housing or a rental interacts with all the coefficients to allow for different coefficients for the same characteristic if the asset class is different. Households can also migrate to an outside asset, which is any PUMA or asset class where the median house value is below \$90k, the monthly median contract rent is below \$200, the median age of the housing stock is 1939 or earlier, or is missing data on any variable in $X_{j,k}$.

To accurately capture geographic and cross-asset class substitution, each origin asset class and destination asset class pair has a different utility "cost" of moving: $\tau_{(i,l)\to(j,k)}$. This is a function of the pairwise distance, the number of social connections from Meta's Social Connectedness Index

(SCI) as used in Bailey, Cao, Kuchler and Stroebel (2018), and a dummy variable for all possible transitions between owning, renting single-family, or renting multifamily housing interacted with a dummy variable for staying in the same PUMA. This allows for total flexibility in substitution patterns between asset classes, across PUMAs, and different substitution patterns across asset classes within the same PUMA compared to across asset classes in separate PUMAs. This flexibility is greater than that of a nested logit specification because each asset class and within or across PUMA transition has its own coefficient, allowing substitution to vary freely with each pair rather than constraining it to a fixed nest structure, and does not impose proportional substitution within nest.

The estimation method in this paper results in realistic spatial and asset class substitution for heterogeneous households in a static setting, by combining migration data that do not have demographic heterogeneity in households, with holdings data with income heterogeneity. Dynamic housing models estimated directly from migration data with household heterogeneity, such as that in Almagro and Domínguez-Iino (2025), obtain accurate spatial substitution for heterogeneous households without having to combine migration data with holdings data. Heterogeneity in moving costs results in the propagation of the institutional investor impact along a network based on empirical moving patterns, similarly to how housing market shocks propagate along search networks in Piazzesi, Schneider and Stroebel (2020). Origin heterogeneity in this paper is similar to the birth-state heterogeneity in Diamond (2016).

Each income group has N_h households. The quantity of homes demanded by households in each location and asset class is therefore:

$$Q_{d,households,i,l} = \sum_h w_{h,i,l} N_h. \tag{9}$$

5.2 Small Landlord Demand

Small landlords react to changes in rents and prices, and therefore their demand for owning homes to rent out adjusts when institutional investors enter the housing market. Each region j has a stock of existing small landlords, $N_{small,j,existing}$, and local households with enough wealth to pay a down-payment of 20%, $N_{small,j,potential}$. The fact that small landlords come from locals with enough wealth to purchase a home is consistent with evidence from this paper that most small landlords are active in only one county, and evidence of home-biased landlords in Levy (2022). An existing or potential small landlord i in region j operates if cash flows from operating are preferred to the cash gained from selling or needed to buy:

$$E\left[\sum_t \frac{(R_{j,t} - C_{i,j,t})}{(1+r_e)^t}\right] \geq P_{j,t} \times (1 - BrokerFee) - M_{i,j,t}. \tag{10}$$

The left-hand side is the expected operating cash flows in each period $R_{j,t} - C_{i,j,t}$ discounted by the cost of equity for those cash flows r_e. The right-hand side is the cash a landlord would obtain from selling a home or the cash needed to buy. The landlord receives or pays the equity position on the home, $P_{j,t} - M_{i,j,t}$ where a broker fee is deducted from the price only if selling (consistent with the structure of the market before 2024). Cash flows from operating each period are expected to grow at a rate of g_j, making this a growing perpetuity. g_j is a function of recent population and job growth in the region, and state-level trends. The cost for a landlord i in a region j is:

$$C_{i,j} = P_j \times PropTax_j + InterestExpense_{i,j} + OtherCosts_i + R_j \times ManagerFee_i. \tag{11}$$

I assume in the model that the typical small landlord has a 30-year mortgage that is paid off over 30 years, is aware of its expected payoff behavior and takes this into account when deciding whether to operate. This is based off of the empirical evidence in Figure B4 covered in previous sections, which shows that small landlords in the RHFS pay off their mortgages over time, are more likely to have a mortgage just after purchase, and Panel D which shows that most small landlords with mortgages have term lengths of 30 years. These assumptions allow the model to capture the fact that some small landlords might barely break even when first purchasing a property because they expect to pay off their mortgage to have larger cash flows in the future. I model small landlords' interest expense as the perpetuity equivalent of the present value of their interest payments. This leads to the decision to operate to be formulated as:

$$R_j \geq (r_e - g_j) \times (P_j \times (1 - BrokerFee) - M_{i,j,t}) + C_{i,j}. \tag{12}$$

In a region j, I aggregate each small landlord's decision to obtain the cost curve:

$$Q_{d,small,j} = \sum_{i \in N_{small,j}} I\left[R_j \geq (r_e - g_j) \times (P_j \times (1 - BrokerFee) - M_{i,j,t}) + C_{i,j}\right]. \tag{13}$$

The aggregate small landlord quantity is increasing in R_j and decreasing in P_j. Decreasing returns to scale comes from heterogeneity in costs of the individual landlords, driven by different interest and operating expenses, which is consistent with empirical evidence in the previous sections.

5.3 *Institutional Investor Demand*

Endogenous large landlord demand that varies with parameters and market structure allows for the modeling of large landlord quantity changes due to mergers, caps on rent increases, and entry with no construction response. A large landlord i chooses a quantity of homes to buy in region j, $Q_{i,j}$ to maximize profits:

$$\max_{Q_{i,j}} \left\{Q_{i,j} \times (CashFromOperating_{i,j} - CashToBuy_{i,j})\right\}. \tag{14}$$

Large landlords buy and renovate homes to receive operating cash flows. They are modeled as Cournot oligopolists, consistent with the empirical evidence that they adjust quantities to maximize profits. They internalize the impact of Q_i on rents and prices given the quantities supplied by others in the market, Q_{other}, which includes quantities from small landlords and other large landlords. Large landlords purchase each home with debt D_t equal to the company-level debt-to-value ratio times the property price. The purchase price of a home depends on whether it is a foreclosure or not. Foreclosures were a critical acquisition channel for institutional investors early on, as documented in Mills et al. (2019) and in SEC filings from INVH and AMH. Among the properties that INVH acquired from September 2015 to September 2016, 37% were acquired through distressed sales, which shows that foreclosures and short sales played an important role in property acquisition even several years after the Great Recession. Each region has a stock of distressed homes available for purchase by large landlords, F_j. Each distressed home can be acquired at a discount, d, therefore altering the acquisition price $P_{acq,j,t}$:

$$CashFromOperating_{i,j} = E\left[\sum_t \left(\frac{R_{j,t}(Q_{other,j} + Q_{i,j}) - C_{i,j,t}}{(1+r_e)^t}\right)\right] \tag{15}$$

$$CashToBuy = P_{acq,j,t}(Q_{other,j} + Q_{i,j}) \times (1 + renovationCost) - D_t \tag{16}$$

$$P_{acq,j,t} = \begin{cases} P_{j,t}, & \text{if } \sum_i Q_{i,j} > F_j, \\ d \times P_{j,t}, & \text{if } \sum_i Q_{i,j} \leq F_j. \end{cases} \tag{17}$$

$$C_{i,j} = P_j(Q_{other,j} + Q_{i,j}) \times PropTax_j + IntExp_i + OtherCosts_{i,j} + ManagementCosts_i. \tag{18}$$

Region-specific costs depend on the local property tax rate. Large landlords' region-specific operating costs are a function of local contractor wages. In contrast to small landlords, large landlords have non-region-specific interest expenses and management costs. Large landlords have the same expected cash flow growth rate as small landlords, g_j, which allows for the modeling of their cash flows as a growing perpetuity. Policies that set a rent growth limit for large landlords will cap g_j for large but not small landlords.

5.4 *Housing Supply*

The quantity of single-family homes in region j, $Q_{j,own,new}$, is determined by the initial value in 2012, $Q_{j,own,2012}$, plus an amount that varies due to increases in the price of housing. I model this as an aggregate construction sector with an elasticity of construction with respect to housing prices for each $PUMA_j$ of γ_j:

$$\log\left(\frac{Q_{j,own,new}}{Q_{j,own,2012}}\right) = \max\left\{\gamma_j \times \log\left(\frac{P_{j,own,new}}{P_{j,own,2012}}\right), 0\right\}. \tag{19}$$

The housing supply cannot shrink if prices go down in this model. Landlords or homeowners can buy the new units.

For γ_j, I use the new-unit supply elasticities with respect to price from Baum-Snow and Han (2024), who provide publicly available census tract–level elasticities. I aggregate the elasticities to obtain the PUMA-level γ_j. Baum-Snow and Han (2024) estimate the elasticities with a finite-mixture model IV that is a function of census tract distance to the nearest central business district, the fraction of land developed in the tract as a linear and quadratic term, the fraction of land in the tract that is flat, metro-area developed land, metro-area land that is unavailable for development because of topography, and the metro-area 2005 Wharton Residential Land Use and Regulation Index value. The model instruments price changes with a Bartik shock constructed from shocks to labor demand in commuting destinations. Elasticities are higher in areas farther from city centers, areas where more land is flat, and areas where regulation is less restrictive.

The supply of rentals in each region j is determined by the sum of the demand of small and large landlords to own homes and operate them. There is a multifamily rental asset class in the model that has perfectly inelastic supply.

5.5 *Market Clearing*

Prices are implicitly defined by market clearing, which I rewrite as a function in logarithms and in vectors below:

$$\mathbf{p} = f(\mathbf{p}) = \log\left(\mathbf{P} \cdot \left(\mathbf{Q}_{d,\text{households}} + \mathbf{Q}_{d,\text{small landlords}} + \mathbf{Q}_{d,\text{large landlords}}\right)\right) - \log(\mathbf{Q}_s). \tag{20}$$

Landlords cannot rent properties from other landlords in this model. An equilibrium is characterized by a price vector for each asset and quantity vector for each agent at which supply equals demand for each asset. I compute counterfactual prices with the Newton's method algorithm from Koijen and Yogo (2019) using a numerical derivative.

6. Estimation

6.1 *Household Demand*

I estimate household demand by first estimating bilateral moving costs $\tau_{(i,l)\to(j,k)}$ and then estimating elasticities to prices, rents, and characteristics for each group with the methods from Berry et al. (1995) and Conlon and Gortmaker (2020). The estimation uses cross-sectional variation from a pool of census PUMAs and bilateral migration data for the whole US from 2012 to 2019.

Step 1: Migration costs. First, I estimate $\tau_{(i,l)\to(j,k)}$. I use migration data from Verisk to construct a dataset of migration shares $w_{(i,l)\to(j,k)}$, which are the fraction of people from (i,l) who move to (j,k), where i and j are PUMAs and l and k are asset classes. I construct migration shares for all movers and nonmovers from 2012 to 2019. Each row is an origin–destination pair. Full details on the construction of this dataset are in Appendix C. I model migration shares to be based on destination characteristics $X_{j,k}$, $p_{j,k}$ which is the log price if k is owner occupied and the log rent if k is a rental, and origin–destination pair characteristics $T_{(i,l)\to(j,k)}$:

$$w_{(i,l)\to(j,k)} = \beta_{p,k}p_{j,k} + \beta_{x,k}X_{j,k} + \beta_t T_{(i,l)\to(j,k)} + \varepsilon_{(i,l)\to(j,k)}. \tag{21}$$

The origin–destination pair characteristics include distance, the SCI for the pair of PUMAs, and interactions between all possible asset class transitions and a same-PUMA indicator variable. The destination characteristics are the same in the estimation of migration costs and household demand, as detailed in the previous section. I estimate equation (21) on the intensive margin with linear IV. Details on instruments follow the description of step 2 which uses the same instruments. I recover estimates for β_t and use them to create the moving costs in utility terms:

$$\hat{\tau}_{(i,l)\to(j,k)} = \hat{\beta}_t T_{(i,l)\to(j,k)}. \tag{22}$$

Step 2: Household demand. Once the $\hat{\tau}_{(i,l)\to(j,k)}$ have been estimated, I partition the right-hand side of (7) into two terms:

$$u_{h,(i,l)\to(j,k)} = \delta_{h,j,k} + \hat{\tau}_{(i,l)\to(j,k)}. \tag{23}$$

Equation (8) becomes:

$$w_{h,j,k} = \sum_{i,l} \frac{\exp(\delta_{h,j,k} + \hat{\tau}_{(i,l)\to(j,k)})}{1 + \sum_{(m,s)} \exp(\delta_{h,m,s} + \hat{\tau}_{(i,l)\to(m,s)})} w_{h,i,l}. \tag{24}$$

I estimate the $\hat{\delta}_{h,j,k}$ with the fixed-point algorithm from Berry et al. (1995). Finally, I estimate the following equation by linear IV to recover price and rent elasticities:

$$\hat{\delta}_{h,j,k} = \beta_{h,p,k}p_{j,k} + \beta_{h,x,k}X_{j,k} + \xi_{h,j,k} + \varepsilon_{h,(i,l)\to(j,k)}. \tag{25}$$

I constrain $\beta_{h,p,k} < 0$ to ensure that demand is downward sloping. If two PUMAs are identical except for price, an agent would prefer the cheaper one. An estimation that results in an agent favoring PUMAs with higher prices can be interpreted as prices covarying with something desirable to households that is outside the model. I estimate equation (25) separately for each income group for the panel of yearly housing holdings from 2012 to 2019 from the census PUMS data in a pooled regression. I do this on the extensive margin by adding one household to each region, resulting in tiny weights in regions where a given household group does not rent or own.

Identification. I estimate household migration equation (21) and household demand equation (25) with linear IV. The challenge to estimating household demand is that prices and rents may be correlated with household latent demand. Positive correlations would make households appear less elastic, amplifying the price and rent effects of demand and supply shocks in the counterfactual estimations. I instrument for prices and rents in a PUMA with features of the housing stock and topography of neighboring regions, similarly to Bayer, McMillan and Rueben (2003), Bayer et al. (2007), and Calder-Wang (2022), and then validate the use of these instruments in my setting. The identification assumptions are that for a given PUMA's price and rent, the characteristics of neighboring regions, $Z_{neighbor,j}$, affect own region price and rent through a competition channel but are far enough away that they do not affect a household's utility of living in a PUMA, once own-region characteristics and longer distance characteristics, X_{long}, are controlled for:

$$E[\varepsilon_{household,(i,l)\to(j,k)} Z_{neighbor,j} | X_{j,k}, X_{j,long}] = 0. \tag{26}$$

As instruments, I use the topography of land 3–10 miles away when controlling for topography within 3 miles. I construct the topography measures using the ZIP code–level land unavailability measures from Lutz and Sand (2022), which describe how much water is in each ZIP code, how much of the ZIP code is covered by wetlands, and the overall unavailability of land in a ZIP code due to topography (which also includes slope). Details for mapping the ZIP code data to the PUMA level are described in the Appendix C. I use three other instruments that are average values of housing stock characteristics of neighboring PUMAs: Median age of the housing stock, median number of bedrooms per home, and fraction of housing in the regions that is single-family.

Long distance phenomena used as controls are distance to the nearest city, distance to the nearest top 30 city, and distance to the nearest coast (including the Great Lakes).

I support the use of these instruments in my setting by examining the results of the first stage of the IV regression of equation (25) in Appendix Table B5. The F statistics for the instruments are 909.0 for log(price) and 1405.9 for log(rent). If neighboring region characteristics affect prices and rents through competition, rather than households having direct utility over characteristics 3-10 miles away, we would expect them to have different relationships to prices and rents in a regression. For log rents, all three topography features for the within-3-mile PUMA area have signs opposite those of the corresponding features for the 3–10 mile ring. Greater land unavailability in neighboring regions is associated with higher rents, illustrating the competition channel: If it is harder to build nearby, rents are higher. For log prices, land unavailability in neighboring regions due to water is associated with higher prices, and the variable has the opposite sign of land unavailability due to water within 3 miles. The statistical significance and opposite signs suggest that neighboring regions' characteristics are relevant and affect price and rent through a different channel from the one through which own PUMA characteristics affect price and rent.

I examine the instruments spatially in Figure B8. Panel A shows the mean land unavailability due to water within 3 miles for each PUMA in Georgia, Panel B the mean land unavailability due to water 3–10 miles away, Panel C the difference between Panels B and A, and Panel D log house prices. PUMAs near the city center have greater land unavailability due to water in neighboring regions than land unavailability due to water in their own region. This is correlated with higher housing prices, which could suggest that land in the city center has high prices because it is harder to build nearby. There are a number of alternative explanations for this correlation in the regression related to longer range phenomenon, including high prices near ports, or high prices near city centers that are related to former ports, or high prices near beaches, which all could drive a correlation between high prices and a lack of land nearby but not in the immediate vicinity. I control for distance to city center, distance to top 30 US city, and distance to the nearest coast in these regressions, so the differential impact of neighboring topography relative to that of own topography on prices and rents must remain after these longer range effects are accounted for.

While the main identification concern is that prices and rents are correlated with household latent demand, and not landlord demand because I am not estimating large landlord demand with IV, it is still possible that large landlord demand is correlated with household latent demand in a way that is also correlated with the instruments, even after controlling for observables. I estimate a leave-out specification where I drop all PUMAs where institutional investors have 200 or more units. This excludes 15% of PUMAs from the estimation and covers 81% of institutional investors' units. I compare price and rent coefficients from the IV, the leave-out specification, and the OLS in Tables B7 and B8. Coefficients for the IV specification are more negative than the OLS, supporting that the instrument is able to deal with some correlation between price and household latent demand. Coefficients for the leave-out specification are broadly similar to the OLS for rentals, and similar to the IV for owner-occupied housing. I examine the sensitivity of the results of the paper to these parameters later in the paper in Figure 14, which shows that headline results directionally hold as long as renters dislike paying rent at all elasticities, and that households and small landlords dislike paying more for housing at a large range of elasticities.

Estimation results. Table B6 shows the estimation results for equation (21). People are more likely to move to PUMAs nearby with many social connections, other asset classes within the same PUMA, and other PUMAs within the same asset class. To validate that this estimation results in rich model substitution patterns of households across geographies and asset classes, and within a geography and across asset classes, I simulate a counterfactual where I raise the price of owner-occupied housing in one PUMA in the suburbs of Atlanta by 10% and keep the rental supply constant. I compare the share of people leaving the PUMA in the simulation to endogenous migration shares in the observational data in Figure B9 Panel A, and the shares of household holdings with endogenous migration shares in the observational data in Panel B. The model matches that substitution from owner-occupied housing to rental housing in the same PUMA is substantially higher than substitution to rentals in other PUMAs, in a way that would not follow if substitution patterns were dictated only by shares of holdings. The correlation between model substitution patterns in this simple simulation and endogenous migration shares is 66%, while the correlation between household holding shares and endogenous migration shares is only 24%.

Figure B10 shows the moving elasticities for each income group with respect to prices and rents from the estimation of equation (25), and Tables B7 and B8 show the full estimation results for rental housing and owner-occupied housing respectively. These elasticities reflect the percentage of a group that will leave for a different PUMA, not the percentage that will leave a house. Someone who stays in the PUMA but downgrades when faced with a price shock would be recorded as inelastic here. Therefore, the elasticities will be lower in magnitude than elasticities for housing units. Approximately 80% of US counties have a population less than the minimum PUMA population,[7] and therefore, a household leaving its PUMA would in most cases be making a larger move than a household leaving its county. The moving elasticities are sufficient to study the PUMA level price impacts of institutional investors.

The moving elasticity with respect to a PUMA's rent for the lowest income households is -1.9, and increases towards 0 for the highest income groups. The moving elasticity for the price of owning housing is -0.42 for the lowest income group and increases towards 0 for the highest income groups. The pattern that sensitivity to prices and rents decreases with income is consistent with results from Diamond (2016) that workers without college experience are more responsive to rents (elasticity of -2.4) than workers who have been to college (elasticity of -1.3). Albouy, Ehrlic and Liu (2016) find aggregate elasticities of approximately -0.7 for renters and -0.5 for owners. Functionally, low moving elasticities for high-income groups mean that, in the model, when large landlords shock the market, residents making 100k+ will not leave for a different PUMA. Residents making 100k+ are constrained to have a $\beta_p,\ \beta_r = -0.001$ to ensure they have downward sloping demand. I further validate the estimation results by comparing my model outputs of price responses resulting from estimated elasticities with those at aggregated geographies in other papers. My price impact for a 1pp demand shock in a given PUMA is 1.7pp when builders can respond, and 4.2pp when construction is shut down. Schubert (2021) finds an elasticity of house price growth of 4.6pp in the short run and 3.4pp in the long run at the commuting zone level in response to a 1pp net inflow of population. While elasticities in this paper are not directly comparable to those in other papers due to different geographies, the estimated elasticities contain patterns that are supported in other studies, and lead to aggregate price multipliers of similar magnitudes to other studies.

6.2 *Small Landlord Demand*

I calibrate the small landlord demand for each region in equation (13) by sampling from the distributions of small landlord operating costs and mortgage balances. For existing landlords, I

[7] County sizes.

sample $N_{small,j,existing}$ times from the distributions for landlords who bought up to 2012, where $N_{small,j,existing}$ is the number of single-family rentals in region j in 2012. For potential landlords, I sample $N_{small,j,potential}$ times from the distributions for landlords who bought between 2013 and 2019. $N_{small,j,potential}$ is the number of households in a PUMA who can afford to pay a 20% down-payment on a $200,000 home. I impute the household wealth distribution from the census ACS in 2012 by dividing the dividend, interest, and rental income by an expected return of 5%. I then require households to have 4x the wealth needed to afford the down-payment, where the multiple is set to target small landlord quantities in the data.

Region-specific parameters. Each small landlord in a PUMA pays the same property tax rate $PropTax_j$, calculated from the property tax rate on sold properties from the Verisk data. I construct a PUMA-specific empirical mortgage balance distribution to calibrate $InterestExpense_{i,j}$ and $M_{i,j}$. For each PUMA, I observe small landlord mortgage origination amounts in the Verisk data. For existing small landlords, I use the November 2015 property data and select properties purchased in 2012 or earlier because the November 2015 cross section is the earliest in the dataset. For potential small landlords, I use the November 2019 property data and select properties purchased after 2012. I calculate mortgage balances outstanding by assuming 30-year terms and linear amortization. From this, I calculate the interest expense as the perpetuity equivalent of the present value of interest payments. I use the observed median small landlord interest rate of 5.25% from the data. Full details are described in Appendix C. Figure B11 shows the significant regional heterogeneity in small landlord average mortgage balance outstanding. The figure also shows that institutional entered the market in regions with high small landlord leverage, which is consistent with the fact that they bought a large number of their homes through distressed sales.

I calculate the expected cash flow growth in each region, g_j, in two steps. I first run a regression of rent growth from 2006 to 2012 at the PUMA level on an indicator variable for above-median national population growth from 2006 to 2012, an indicator variable for above-median annual job growth from 2004 to 2013 from the Opportunity Insights data, and state fixed effects:

$$g_{j,s} = \beta_{pop} I \left[\Delta pop_{j,s} \geq Med.\Delta jobs_{j,s} \right] + \beta_{jobs} I \left[\Delta jobs_{j,s} \geq Med.\Delta jobs_{j,s} \right] + \alpha_s + \varepsilon_{j,s}. \tag{27}$$

I recover $\beta_{pop} I\left[\Delta pop_{j,s} \geq Med.\Delta jobs_{j,s}\right]$, $\beta_{jobs} I\left[\Delta jobs_{j,s} \geq Med.\Delta jobs_{j,s}\right]$, and α_s for each PUMA and then set the mean of this resulting distribution to 4%—the 5-year expected rent growth from the New York Federal Reserve Bank's Survey of Consumer Expectations (SCE) data for 2014, the earliest year of publicly available SCE data. Landlords assume that a PUMA above the median in each category will continue to be above the median, that the relationship of these variables with rent will stay the same, and that state-level trends will stay the same. Both small and large landlords have the same expected rent growth, which for Georgia has a range of 1.8%–5.7%, as shown in Figure B12.

Non-region-specific parameters. For each PUMA, non-region-specific costs $OtherCosts_i$ and $ManagerFee_i$ come from a national distribution of operating costs constructed with data from the RHFS. I create a dataset of small landlord cost components from the RHFS as described in Appendix C. For each PUMA's small landlords, I sample from this distribution operating costs excluding interest and property taxes $N_{small,j}$ times to obtain the PUMA landlords' operating costs and manager fees as a function of region-specific rent. For all PUMAs, I set $BrokerFee$ to 6% for existing landlords and to 0% for potential small landlords, which is standard.[8]

To obtain r_e, I assume that small landlords have the same asset betas as INVH and AMH from their IPOs to 2024, and I set their required rate of return to what it would be if they had zero leverage. I apply the capital asset pricing model to the unlevered total return betas from INVH and AMH, which leads to 5.2%, which I round down to 5%. There is evidence that small landlords like cash flows from rentals more than would be expected. In the RHFS data, a large number of small landlords are operating at an apparent loss, even if we don't consider interest expenses or the opportunity cost of capital at all. This choice of r_e at 5% is used to target the number of small landlords operating. Varying r_e changes the number of small landlords operating, but does not largely change their elasticities, which are the parameters that matter for the model.

Estimation results. To measure the fit of the small landlord estimation procedure, I estimate small landlord demand with observed 2012 rents and prices. I compare the results with observed quantities in Georgia and in the PUMAs within Georgia where institutional investors combined

[8] Real estate commission rates.

own over 1000 homes. The results in Table B9 show the estimated and actual quantities are highly correlated. The levels are accurate for Georgia and a slight overestimate for the subset of Georgia PUMAs where institutional investors are most active. In the model, a residual Ξ_j makes up for the difference to match the 2012 housing market exactly:

$$Q_{d,small,j} = \sum_{i \in N_{small,j}} I\left[R_{j,t} \geq (r_e - g_j) \times (P_{j,t} \times (1 - BrokerFee) - M_{i,j,t}) + C_{i,j,t}\right] + \Xi_j. \tag{28}$$

What matters for the model is not the quantity of the estimate, because the residual makes up for this, but the slope of the supply curve where it intersects demand. Small landlords are less sensitive to changes in prices and rents in PUMAs with high institutional investor activity.

I examine the elasticities with respect to price resulting from the calibration by raising housing prices by 1% in each PUMA in Georgia, and then regressing the quantity changes on a number of characteristics. Results in Table B10 show that small landlords' sensitivity to price decreases with high expected rent growth and increases with high price-to-rent ratios and high PUMA leverage. PUMAs with many institutional investors have low price-to-rent ratios and high expected rent growth, therefore the small landlords in these regions are less sensitive to prices.

6.3 Large Landlord Demand

While property taxes and expected rent growth rates are the same for both landlord types, large landlords have different operating costs, interest expenses, management costs, renovation costs, and discount rates. For operating costs, I use AMH's 2014Q1 average market cost and subtract property taxes, which is the earliest period I have operating cost data for the large landlords. I then apply a cost shifter for regional contractor wages, which are correlated with costs in different markets. I estimate this cost shifter with a regression of market-level operating expenditures on state-level contractor wages from the Bureau of Labor Statistics Quarterly Census of Employment and Wages. I use a renovation cost of 10%, a 65% debt-to-value ratio from INVH's early time periods, and choose r_e to be 16% based on conversations with operators who target IRRs of 16–20%. While the IRR is not a hurdle rate, a company targeting a given IRR may select to use it as a hurdle rate. The discount rate helps the model match the aggregate number of large landlord units. Changes affect aggregate quantities but do not broadly change location choice.

The distressed acquisition discount is calibrated to be within empirical findings and match the total number of homes purchased by large landlords. Campbell, Giglio and Pathak (2011) finds a foreclosure discount for single-family homes of 22%. Mayer (1998) finds a real estate auction discount of 0-9% in Los Angeles and a discount of 9-27% during a bust. Zhou, Yuan, Lako, Sklarz and McKinney (2015) finds an average discount of 15% that is significantly smaller for newer properties. Conklin, Edward Coulson, Diop and Mota (2023) finds foreclosure and short sale discounts averaging 5-6%. Given that institutional investors focused on newer properties that did not require significant maintenance from 2012 onward, and that institutional investors bought both foreclosures and short sales, I use a discount of 10%.

I set the number of distressed homes in each region available for purchase by institutional investors equal to 5% of the total number of foreclosures in each region from 2007–2011 to match the total number of homes purchased by investors and reflect that many of these were purchased up by others. This results in an additional test of the model: Its ability to match the fraction of distressed purchases made by institutional investors. Institutional investors in the model purchase 37% of their homes through distressed channels. AMH in its 2015Q4 earnings statement supplement, which is the last earnings statement supplement that distinguishes acquisitions by buying channel, acquired 34,076 homes from 2012Q2 to 2015Q4. 48% of these acquisitions were through trustee sales, where trustee sales typically indicate distress. INVH in its IPO filings wrote that in 2014, 2015, and 2016 it acquired 52%, 44%, and 37% respectively of its homes through distressed channels not including bulk sales. Growth after 2016 due to mergers would average the distressed purchase fractions on existing units. Organic growth would have a lower distress rate due to decreased prevalence of foreclosures farther from the financial crisis. The model output of 37% of distressed purchases is a reasonable match considering higher numbers of early foreclosure acquisitions with lower numbers of later foreclosure acquisitions.

I show the large landlord estimation results spatially in Figure B13. Panel A shows the estimated quantities for 3 identical large landlords and Panel B the actual quantities for institutional investors in 2019. In 2021, the mean number of institutional investors in a PUMA where the investors have at least 10 units each was 3. The spatial pattern is similar for both the estimated and actual quantities. The estimated total number of units in Georgia is 25,104 and the actual number is 21,566. The model over-predicts entry in regions with foreclosures that are not near their central cluster of regions, which are cheap to buy homes in, but may have too few homes to reach a sufficient spatial density for operations.

6.4 Housing Supply

I construct a PUMA level aggregate builder supply elasticity by mapping the 2011 tract level estimates of new unit supply elasticities from Baum-Snow and Han (2024) from 2000 census tract geographies to 2010 tract geographies, and then aggregating them up to the PUMA level, weighted by the number of homes in each tract. The resulting elasticities are heterogeneous across PUMAs, as shown in Georgia in Figure B14. Missing elasticities are imputed with state-level means (0.22 for Georgia). Most PUMAs with missing values are not areas where institutional investors entered.

7. Impact of Institutional Investor Entry

7.1 Model Results

I estimate the equilibrium impact of 3 identical large landlords who enter the housing market in Georgia in 2012 and choose where to operate and how many units to operate in each PUMA. I implement the Newton step algorithm from Koijen and Yogo (2019) to recover market-clearing prices, rents, and quantities.

I begin by analyzing the impact of institutional investor entry on the number of homes available for homeownership. Institutional investor entry decreased homeownership by 0.22 homes for each home purchased. The impact of the investors on homeownership is significantly less than 1:1 because of two supply responses shown in Figure 7 Panel A. When an institutional investor purchases a home, this puts downward pressure on the number of homes for owner occupancy by 1. However, the institutional investor demand shock raises prices, which causes builders to build 0.28 homes. Institutional investors also lower rents due to increasing the supply of rentals. The increase in prices and decrease in rents causes small landlords sell 0.5 homes. A back-of-the-envelope calculation of the impact of institutional investors on homeownership that fails to incorporate the supply responses would overestimate the impact by a factor of 5.

In the rental market, Panel B shows that institutional investors increase the number of homes available to rent by 0.5 homes for each home that they purchase. The estimation, which includes both the incentive to use market power and the operating efficiency of land landlords, shows that the economies of scale outweigh the incentive to use market power to decrease rental supply, leading to a net increase in the rental supply. The increase in rental supply is less than 1:1 due to the crowding-out of small landlords, who sell 0.5 homes. This corresponds to a crowd-out ratio of 0.5 , far below the crowd-out ratio of 1 required for institutional investors to increase rents.

Evidence in the correlational data supports that institutional investors increased the rental supply and crowded out other landlords. With the Verisk data, I first examine the association of the change in institutional investor units in a census tract from November 2016 to February 2021, $\Delta Q_{i,cty,tr}$, with the change in units by other landlords in the tract over the same period, $\Delta Q_{other,cty,tr}$. County fixed effects, α_{cty}, control for county level variation. I run the following regression:

$$\Delta Q_{other,cty,tr} = \Delta Q_{i,cty,tr} + \alpha_{cty} + \varepsilon_{cty,tr}. \tag{29}$$

Results in Table B11 show that each unit institutional investors gained is associated with other landlords decreasing their holdings by 0.53-0.63 units, which implies an increase in the rental supply of 0.37-0.47 units for each unit institutional investors purchased. This non-causal crowd-out-ratio is similar to but larger than the model implied impact of institutional investors, possibly because prices rose in these regions for reasons unrelated to large landlord entry. Results for the same regression, split by landlord type, in Figure B16 show that the other largest landlords and small landlords with mortgages tend to leave when large landlords enter the market. The largest other owners tend to decrease their holdings because institutional investors merge and buy from other large landlords, and also because they buy foreclosed homes which can appear in the data as coming from large portfolios of foreclosed homes. The smallest landlords with mortgages leave, which is consistent with the model predictions that highest cost small landlords, those with mortgages, would be the first to leave as prices increase. I also examine who institutional investors buy from directly. While I do not have transaction-level data, the property-level data contain information related to the most recent sale of each property. I am able to examine approximately 17,000 purchases by institutional investors from 2017–2021 and find that 44% of their purchases are from owner occupants and 56% are from non-owner occupants. This is consistent with results in Gorback et al. (2024) which finds that institutional investors buy 39% of their properties from owner occupants and 61% from non-owner occupants. Additionally, a binscatter of the change in number of rental households from the Census ACS 1-year tables at the PUMA level and institutional investor presence in observational data in Figure B15 shows that where institutional investors own more of the rental supply, the number of renters increased from 2012–2019 relative to the rest of the country.

I examine whether the increase in the rental supply due to institutional investor entry increases neighborhood access for the financially constrained. Figure 8 shows the model output of the number of owner-occupied homes and rentals that each income group gains or loses when the institutional investors enter. Households with incomes between $25k and $50k lose the most homes for owner occupancy because homeowners with incomes in this range are most exposed to the institutional investor shock. By supplying rentals, institutional investors increase the rental supply for the lowest-income renters, whose elasticity to changes in rents is highest. The results are consistent with the descriptive analysis, which showed that the renters who moved into institutional investor homes came from areas with lower median household incomes.

The institutional investor demand shock increased prices by 1.7pp per 1 pp of the total housing stock in a PUMA purchased. Figure 9 Panel A shows the model-implied impact of institutional investor entry on home purchase prices by the share of a PUMA's housing stock that the institutional investors purchase, and the data association between institutional investors and actual price increases in excess of the rest of the US from 2012 to 2019. The model-implied impact is significantly smaller than the data association, suggesting that the investors targeted regions where prices would have gone up had they not entered. The impact is economically meaningful in the regions where institutional investors purchased the most homes: In the top decile of PUMAs by institutional investor purchases, conditional on institutional investor entry, prices increased by 6.2%, which on a $300k home is $18,600. The model-implied impact is not monotonically increasing in the institutional investor share because each PUMA has a different price elasticity because of the heterogeneity among the PUMA's residents and a different builder elasticity. For the majority of regions where institutional investors entered, almost all of the observed price association is not attributable to these investors. Additionally, these investors entered only a small portion of the country and are not responsible for the broad price increases in the US over this time period.

Institutional investor entry decreased rents on net because they increased the supply of rentals. Figure 9 Panel B shows the model-implied impact of institutional investor entry on single-family rents. The x-axis shows the share of a PUMA's single-family rentals supplied by institutional investors after entry. Institutional investors decreased rents by 0.7pp per 1 pp of the total rental stock that they own. The model-implied rent impact is of opposite sign to that observed in the data, suggesting that rents would have risen in the absence of institutional investor entry. This impact incorporates both the investors' market power and their operating efficiency. The investors are sufficiently efficient operators that even with market power, they increase the number of rentals and decrease rents. If policymakers were to consider only the market power channel, they would get the direction of institutional investors' impact on rent wrong.

The price increase led to capital gains for homeowners who held housing during this increase. The model implied capital gains shown in Figure 10 are largest for high and middle income households. The middle-income households were the most exposed to the price impact, but were also more likely to sell their homes. High-income homeowners were not as exposed but did not move in response to investor entry.

I examine whether it is likely that the observed price and rent increases in regions where institutional investors entered were attributable to institutional investors' targeting of regions where prices and rents would have risen without their entry. With data from the ACS, Figure B2 Panel C shows that the areas where institutional investors purchased homes experienced outsized population gains compared to the rest of the country. Institutional investors in their IPO filings indicated that they targeted areas with expected population growth in anticipation of correspondingly higher price and rent appreciation.[9] The shape of the population curve matches the shape of the price and rent associations in Figure B2 Panel A, suggesting that population growth, not the presence of institutional investors, may have caused the price and rent increases. If institutional investors had caused the increases in prices and rents, we would expect to instead see increasing price and rent increases with institutional investor concentration.

[9] AMH form S-11, page 7 and INVH form S-11, page 4.

7.2 Economic Channels

To test the market power channel, I simulate a merger between two of four large landlords who enter the housing market in the model. I compare quantities, rents, and prices when 3 large landlords enter the market to when 4 enter the market, which simulates a merger with no adjustment costs. I plot the changes in rents and quantities by PUMA in Figure 11. In the mean PUMA with institutional investor overlap, single-family rents increase by 0.6%. Panel A shows this is increasing in the share of rental housing owned by the institutional investors. This magnitude is consistent with that measured in Gurun et al. (2022), which uses quasi-experimental variation from mergers of large landlords and finds a rent impact of 0.5% in the region of overlap. The effect in my setting may be larger due to the lack of adjustment costs.

Market power here is exercised by operating fewer rental properties, due to the modeling of these companies as Cournot oligopolists, consistent with empirical evidence. In Panel B, I show the change in the number of single-family rentals due to the merger: The quantity of single-family rentals decreases by a mean of 0.4% in the regions with overlap between the merged companies and is decreasing in the market share of the institutional investors. Institutional investors face a larger residual demand over which they are monopolists when there are fewer of them, and therefore decrease their quantities to maximize profits. Figure 12 shows graphically that a merger would move the equilibrium from 4 to 3, raising rents and decreasing quantities. The decrease in quantities releases units back into the housing market and therefore lowers house prices as shown in Figure 11 Panel C and increases the quantity of homes held by homeowners, as shown in Panel D. Mergers in this setting benefit prospective homeowners because the merged entity does not increase vacancies as the result of an increase in market power due to the merger.

I examine the role of the construction response by estimating the impact of institutional investor entry when the supply of homes is not allowed to adjust. The price impact would be 2.5 times as large if there were no construction response: 4.2 pp per 1 pp of housing stock purchased by the institutional investors in a PUMA. This is shown at the PUMA level in Figure 13. The quantity of homes available for homeownership in this scenario decreases by 0.4 homes for each home purchased, rather than 0.22, which is a homeownership impact almost twice as large as the baseline. This suggests that supply responses play an important role in mediating the price and homeownership impacts of institutional investor entry. Similar-sized demand shocks to regions with less elastic supply would cause larger price impacts.

The crowd-out ratio increases when there is no construction to 0.6 from the baseline of 0.5. I show how the crowd-out ratio varies in terms of key estimated parameters in Figure 14. I convert the estimated price multiplier due to institutional investor entry, mean elasticity of households with respect to rents, and mean elasticity of small landlords with respect to marginal costs which are all in percentage terms into linear terms to use in the formula for the crowd-out ratio in the stylized linear model. I choose a value for e of 9% of purchase value per year, which corresponds to a property tax component, insurance, repairs that are a function of price, and the opportunity cost of owning the home. Panel A shows that the crowd-out ratio is increasing in the price multiplier because the more prices increase, the more large landlord entry increases costs for small landlords. The multiplier is a decreasing function of the sensitivity of households, small landlords, and builders to purchase prices. The crowd-out ratio is decreasing in builder supply elasticity, as indicated in the shift from the baseline estimate to the no construction estimate. Panel B shows that the crowd-out ratio is decreasing in the sensitivity of households to rents. If when large landlords enter and increase the supply, elastic renters come to fill in the gap, then rents do not decay by as much due to the new supply, which small landlords like. Panel C shows that the ratio is increasing in the fraction of purchase price small landlords must pay in marginal cost, which is proportional to the amount that large landlords raise costs for small landlords. Panel D shows that the crowd-out ratio is increasing in how sensitive small landlord quantities are to marginal cost increases. The variation of the crowd-out ratio with respect to parameters highlights that for large landlords entry to increase rents, they must raise costs for small landlords substantially and small landlords need to be sensitive to these cost increases. Both the baseline and no construction scenarios are far from reaching a crowd-out ratio of 1, which is required to reverse the results for large landlord entry to raise rents.

7.3 Policy Simulations

Next, I simulate two government policies: a large tax on institutional investors that effectively bans them from operating single-family rentals, and a cap on annual rent increases that applies only to corporate landlords.

The first simulation aims to determine the effects of the End Hedge Fund Control of America Act, and the American Neighborhood Homes Protection Act. Both would impose a tax of either $10,000 or $50,000 per home per year for each single-family rental above either 50 or 75 that a landlord owns. The smaller tax, the $10,000, would more than double the operating costs of AMH and INVH and make them unprofitable, therefore effectively banning them from the market. I simulate these policies by removing institutional investors from the market entirely.

I estimate the structural model of housing demand and supply to match 2019 exactly, then remove the 7 large landlords from the descriptive analysis from the homes in their exact footprint from 2019, and do not allow the built housing supply to contract. I show the impact on prices in Figure 13. Prices decrease by 6.2pp per 1pp of the housing stock that institutional investors own, and rents increase by 0.7pp per 1pp of the rental housing stock in a PUMA that they own. Among the homes vacated, 64% go to small landlords. The End Hedge Fund Control of American Homes Act requires that large landlords sell only to households, not landlords. This would lead to all of the homes going to households, but the price decreases and rent increases would be even larger.

I also simulate a 5% annual rent increase limit for corporate landlords by taking the estimated structural model for 2012 and capping the expected rent growth for large landlords at 5%. Institutional investors buy 25% fewer rentals. I show the changes in rents and quantities relative to the baseline in Figure 15. Rents are higher relative to the no rent increase cap counterfactual in regions where large landlords expect this cap to be binding because large landlords decrease quantities in regions. The decrease in rental supply due to rent stabilization is consistent with results from Diamond, McQuade and Qian (2019) and Favilukis, Mabille and Van Nieuwerburgh (2022).

Both policies would decrease the quantity of rentals supplied by large landlords, lower the rental supply, and increase rents. The policies would be counterproductive in the rental market because they are designed to decrease rent increases from market power, and do not account for the fact that large landlords have on net increased the rental supply and decreased rents.

8. Conclusion

This paper estimates the impact of institutional investors entering the single-family rental market for the first time since 2012. It develops a structural model with landlord type heterogeneity in operating costs and market power, and then simulates institutional investor entry into the housing market where households, small landlords, and construction can respond. The paper provides a framework for thinking about the different channels through which institutional investors can affect the housing market, and a way to think about market power in single-family rentals. I find that institutional investors increase the quantity of rentals and lower rents on net because their ability to operate large portfolios at scale outweighs the incentive to use market power to decrease the rental supply. Institutional investors decrease the quantity of homes available for homeownership and raised prices, however the homeownership impact is 1/5th of what it would be if there were no supply response and the price impact is far below the observed association between institutional investor purchases and actual price increases. I find that renters from regions with lower median incomes, worse school test scores, and lower historic economic mobility move into institutional investor rentals. Together the results suggest that institutional investors lowered rents for renters and increased their neighborhood options, caused capital gains for incumbent homeowners, however they increased prices for prospective homeowners.

The findings suggest that most of the association between investors and price growth, and all of the association between investors and rent growth, were not caused by investor demand or market power but instead by investors targeting areas with expected price and rent increases. The results highlight the importance of disentangling selection from causal impact for policy, as policies designed to reduce rents by removing institutional investors would end up increasing rents by shrinking the rental supply. The results also highlight the importance of supply responses in mitigating demand shocks. A large construction response and the crowding-out of small landlords proved of first-order importance in attenuating the effect of investor demand on prices and homeownership. Additionally, large landlords are starting to build more homes to rent out, rather than purchasing homes to rent. Because this paper provides a flexible framework through which one can study many housing market topics featuring heterogeneity in landlord types, construction, and household behavior, future work can study the incentives of landlords to build homes and how build-to-rent affects the housing market.

References

Albouy, David, Gabriel Ehrlic, and Yingyi Liu, 'Housing Demand, Cost-of-Living Inequality, and the Affordability Crisis," Working Paper 2016.

Almagro, Milena and Tomás Domínguez-Iino, 'Location Sorting and Endogenous Amenities: Evidence from Amsterdam," *Econometrica*, 2025, *93* (3), 1031–1071.

An, Brian Y., 'The Influence of Institutional Single-Family Rental Investors on Homeownership: Who Gets Targeted and Pushed Out of the Local Market?," *Journal of Planning Education and Research*, 2023.

Austin, Neroli, 'Keeping Up with the Blackstones: Institutional Investors and Gentrification," Working Paper November 2022.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel, 'The Economic Effects of Social Networks: Evidence from the Housing Market," *Journal of Political Economy*, 2018, *126* (6), 2224–2276.

Barbieri, Felipe and Gregory Dobbels, 'Market Power and the Welfare Effects of Institutional Landlords," Working Paper 2025.

Baum-Snow, Nathaniel and Lu Han, 'The Microgeography of Housing Supply," *Journal of Political Economy*, 2024.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan, 'A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, 2007, *115* (4), 588–638.

_, Robert McMillan, and Kim Rueben, 'An Equilibrium Model of Sorting in an Urban Housing Market: A Study of the Causes and Consequences of Residential Segregation," Working Paper January 2003.

Berry, Steven, James Levinsohn, and Ariel Pakes, 'Automobile Prices in Market Equilibrium," *Econometrica*, 1995, *63* (4), 841–890.

Bertrand, Joseph, 'Review of 'Theorie mathematique de la richesse sociale' and 'Recherches sur les principes mathematiques de la theorie des richesses'," *Journal des Savants*, 1883.

Billings, Stephen B. and Adam Soliman, 'The Social Spillovers of Homeownership: Evidence from Institutional Investors," Working paper 2024.

Calder-Wang, Sophie, 'The Distributional Impact of the Sharing Economy on the Housing Market," Working paper 2022.

_ and Gi Heung Kim, 'Algorithmic Pricing in Multifamily Rentals: Efficiency Gains or Price Coordination?," Working paper 2024.

Campbell, John Y., Stefano Giglio, and Parag Pathak, 'Forced Sales and House Prices," *American Economic Review*, August 2011, *101* (5), 2108–31.

Chang, Konhee, 'Diversifying the Suburbs: Rental Supply and Spatial Inequality," Working Paper 2025.

Chinco, Alex and Christopher Mayer, 'Misinformed Speculators and Mispricing in the Housing Market," *The Review of Financial Studies*, 10 2015, *29* (2), 486–522.

Conklin, James N., N. Edward Coulson, Moussa Diop, and Nuno Mota, 'An Alternative Approach to Estimating Foreclosure and Short Sale Discounts," *Journal of Urban Economics*, 2023, *134*, 103546.

Conlon, Christopher and Jeff Gortmaker, 'Best practices for differentiated products demand estimation with PyBLP," *The RAND Journal of Economics*, 2020, *51* (4), 1108–1161.

Cournot, Antoine Augustin, *Recherches sur les principes mathématiques de la théorie des richesses* 1838.

Coven, Joshua, Arpit Gupta, and Iris Yao, 'JUE Insight: Urban flight seeded the COVID-19 pandemic across the United States," *Journal of Urban Economics*, 2023, *133*, 103489. Special Issue: JUE Insight Shorter Papers.

Desmond, Matthew and Nathan Wilmers, 'Do the Poor Pay More for Housing? Exploitation, Profit, and Risk in Rental Markets," *American Journal of Sociology*, 2019, *124* (4), 1090–1124.

Diamond, Rebecca, 'The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Review*, March 2016, *106* (3), 479–524.

_ , Tim McQuade, and Franklin Qian, 'The Effects of Rent Control Expansion on Tenants, Landlords, and Inequality: Evidence from San Francisco," *American Economic Review*, September 2019, *109* (9), 3365–94.

Ellen, Ingrid Gould and Laurie Goodman, 'Single-family rentals: Trends and policy recommendations," Policy Proposal, Brookings 2023.

Favilukis, Jack and Stijn Van Nieuwerburgh, 'Out-of-Town Home Buyers and City Welfare," *The Journal of Finance*, 2021, *76* (5), 2577–2638.

_ , Pierre Mabille, and Stijn Van Nieuwerburgh, 'Affordable Housing and City Welfare," *The Review of Economic Studies*, 05 2022, *90* (1), 293–330.

Francke, Marc, Lianne Hans, Matthijs Korevaar, and Sjoerd van Bekkum, 'Buy-to-Live vs. Buy-to-Let: The Impact of Real Estate Investors on Housing Costs and Neighborhoods," Working Paper June 2023.

Ganduri, Rohan, Steven Chong Xiao, and Serena Wenjing Xiao, 'Tracing the Source of Liquidity for Distressed Housing Markets," *Real Estate Economics*, May 2022.

Garriga, Carlos, Pedro Gete, and Athena Tsouderou, 'The economic effects of real estate investors," *Real Estate Economics*, 2023, *51* (3), 655–685.

Giacoletti, Marco, Rawley Z. Heimer, Wenli Li, and Edison G. Yu, 'Single-Family REITs and Local Housing Markets," Working paper 2024.

Gorback, Caitlin and Ben Keys, 'Global Capital and Local Assets: House Prices, Quantities, and Elasticities," *Forthcoming, Review of Financial Studies*, 2025.

Gorback, Caitlin S., Franklin Qian, and Zipei Zhu, 'Impact of Institutional Owners on Housing Markets," Working paper 2024.

Gupta, Arpit, Vrinda Mittal, Jonas Peeters, and Stijn Van Nieuwerburgh, 'Flattening the curve: Pandemic-Induced revaluation of urban real estate," *Journal of Financial Economics*, 2022, *146* (2), 594–636.

Gurun, Umit G, Jiabin Wu, Steven Chong Xiao, and Serena Wenjing Xiao, 'Do Wall Street Landlords Undermine Renters' Welfare?," *The Review of Financial Studies*, 03 2022, *36* (1), 70–121.

Hanson, Sebastian, 'Institutional investors in the market for single-family housing: Where did they come from, where did they go?," Working Paper 2024.

Jiang, Zhengyang, Robert Richmond, and Tony Zhang, 'A Portfolio Approach to Global Imbalances," *The Journal of Finance*, 2024, *79* (3), 2025–2076.

Kim, Minjoo, Prateek Mahajan, and Zirui Wang, 'The Rise in Insurance Costs for Commercial Properties: Causes, Effects on Rents, and the Role of Owners," Working Paper 2025.

Koijen, R. S. and M. Yogo, 'Exchange rates and asset prices in a global demand system.," Working paper 2019b.

Koijen, Ralph S. J. and Motohiro Yogo, 'A Demand System Approach to Asset Pricing," *Journal of Political Economy*, 2019, *127* (4), 1475–1515.

Koijen, Ralph S J, Robert J Richmond, and Motohiro Yogo, 'Which Investors Matter for Equity Valuations and Expected Returns?," *The Review of Economic Studies*, 08 2023, *91* (4), 2387–2424.

Kreps, David M. and Jose A. Scheinkman, 'Quantity Precommitment and Bertrand Competition Yield Cournot Outcomes," *The Bell Journal of Economics*, 1983, *14* (2), 326–337.

Lambie-Hanson, Lauren, Wenli Li, and Michael Slonkosky, 'Real estate investors and the U.S. housing recovery," *Real Estate Economics*, 2022, *50* (6), 1425–1461.

Lee, Keyoung and David Wylie, 'Institutional Investors, Rents, and Neighborhood Change in the Single Family Residential Market," Working Paper 2024.

Levy, Antoine, 'Housing Policy with Home-Biased Landlords: Evidence from French Rental Markets," Working paper 2022.

Lutz, Chandler and Ben Sand, 'Highly Disaggregated Land Unavailability," Working paper 2022.

Mayer, Christopher J., 'Assessing the Performance of Real Estate Auctions," *Real Estate Economics*, 1998, *26* (1), 41–66.

McFadden, Daniel, 'Modeling the Choice of Residential Location," *Spatial Interaction Theory and Planning Models*, 1978.

Mills, James, Raven Molloy, and Rebecca Zarutskie, 'Large-Scale Buy-to-Rent Investors in the Single-Family Housing Market: The Emergence of a New Asset Class," *Real Estate Economics*, 2019, *47* (2), 399–430.

Piazzesi, Monika, Martin Schneider, and Johannes Stroebel, 'Segmented Housing Search," *American Economic Review*, March 2020, *110* (3), 720–59.

Raymond, Elora Lee, Richard Duckworth, Benjamin Miller, Michael Lucas, and Shiraj Pokharel, 'From Foreclosure to Eviction: Housing Insecurity in Corporate-Owned Single-Family Rentals," *Cityscape*, 2018, *20* (3), 159–188.

Schubert, Gregor, 'House Price Contagion and U.S. City Migration Networks," Working paper 2021.

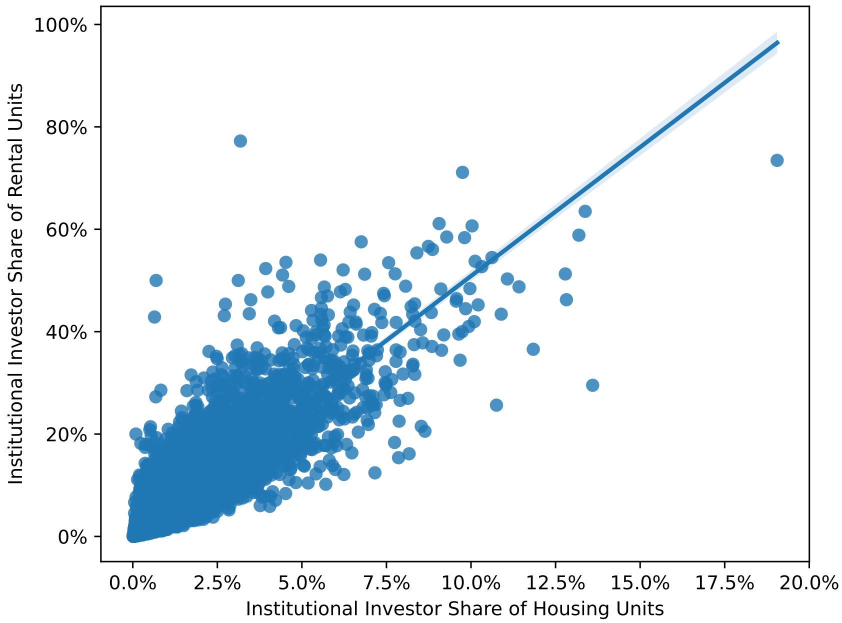
Watson, C. Luke and Oren Ziv, 'A Test for Pricing Power in Urban Housing Markets," Working paper 2024.

Zhou, Hanqing, Yuan Yuan, Christopher Lako, Michael Sklarz, and Charles McKinney, 'Foreclosure Discount: Definition and Dynamic Patterns," *Real Estate Economics*, 2015, *43* (3), 683–718.

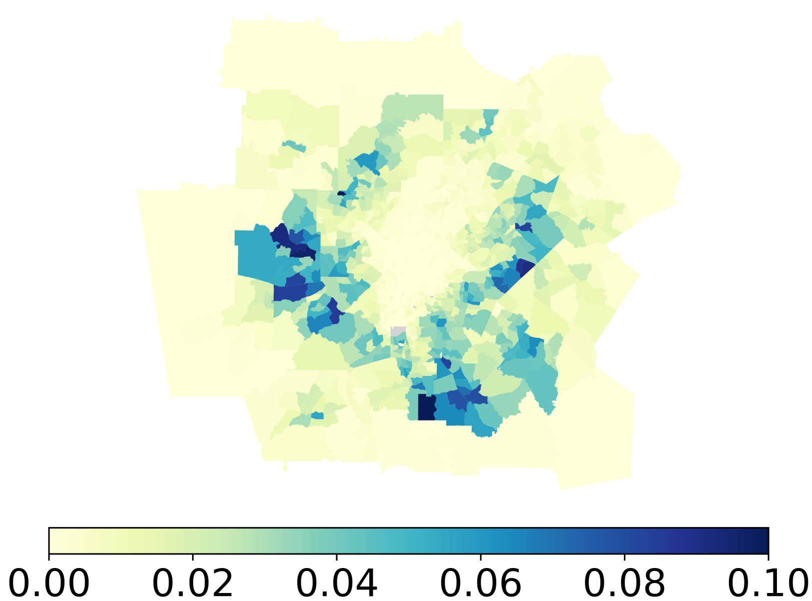
9. Tables and Figures

Figure 1: Institutional investor ownership concentration at census tract level (2021)

Panel A: Fraction of rentals owned vs housing units owned in the US



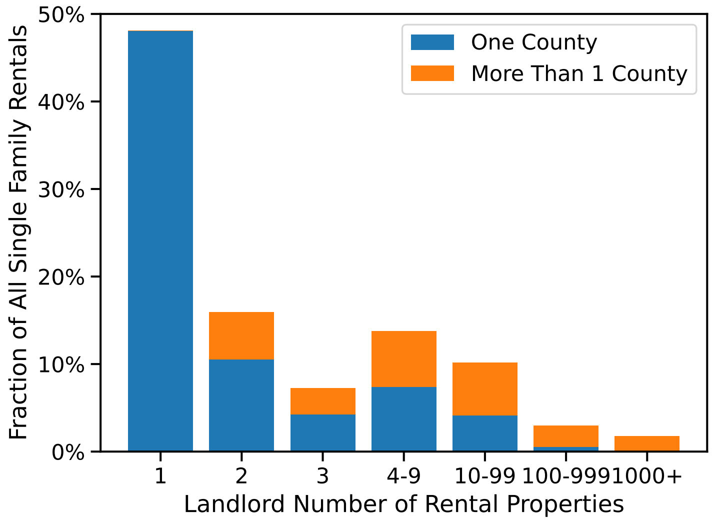
Panel B: Fraction of housing units owned in Atlanta



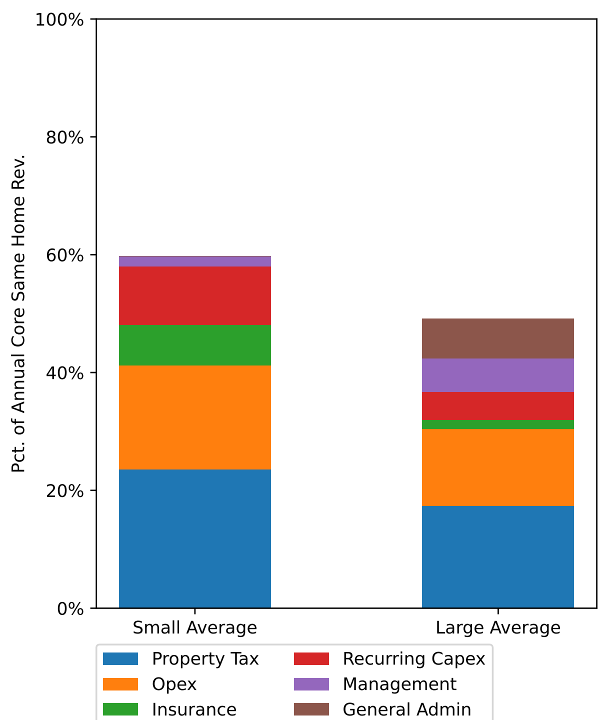
Notes: Panel A plots the fraction of the housing stock in a census tract owned by the 7 largest institutional investors in February 2021 against the fraction of the rental housing owned by these 7 investors for all tracts where at least one of the investors is present. Panel B shows the fraction of the residential housing stock in a census tract owned by these 7 investors in the counties including and surrounding Atlanta, Georgia. The investors included are Invitation Homes, American Homes for Rent, Tricon Residential, FirstKey Homes, Progress Residential, Main Street Renewal, and Home Partners of America.

Figure 2: Competitive landscape for single-family rental market

Panel A: Distribution of single-family rentals by operator size



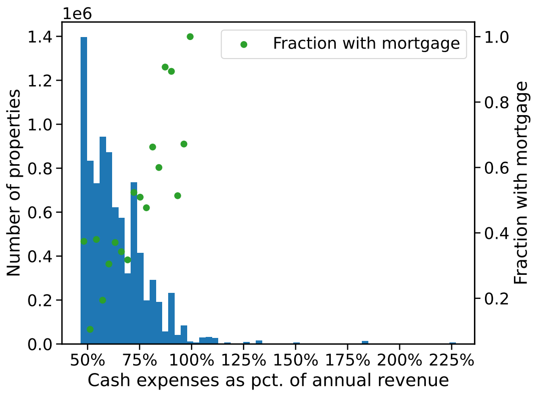
Panel B: Difference between large and small landlord operating costs



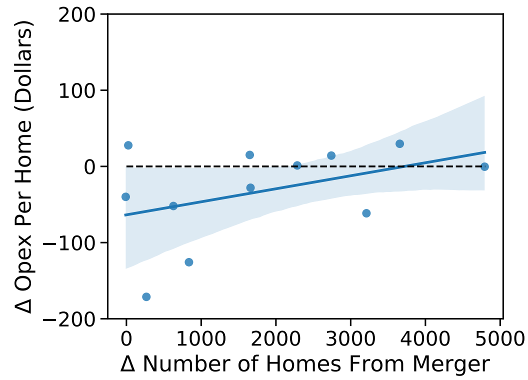
Notes: Panel A shows the fraction of all single-family rentals in the US owned by operators in each size bucket and, within each operator size bucket, the fraction of housing providers that operate in only one county or multiple counties. Data come from a Verisk property snapshot from February 2021. Rental status is determined by whether the mailing address is the same as the property address. Panel B compares operating costs for the average 1-unit individual landlord in the Rental Housing Finance Survey to operating costs for the average of Invitation Homes and American Homes for Rent, where data come from their earnings statement supplements. Data are from an average of fiscal years 2017 and 2020. For Invitation Homes and American Homes for Rent, all data except for general admin, management, and insurance costs are from their "same home portfolios," which excludes recently acquired homes or homes in preparation to be sold. For the small landlords, recurring capital expenditure is the capital expenditure for categories that include HVAC, roof, and floor.

Figure 3: Scale comparison of small and large landlords

Panel A: Cost heterogeneity for small landlords



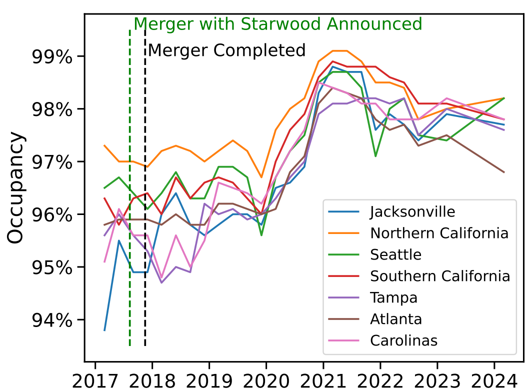
Panel B: Change in opex per home from INVH–SWH Merger



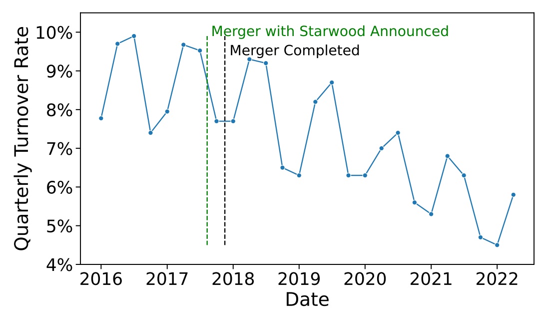
Notes: Panel A shows a histogram of individual 1-unit landlords in the Rental Housing Finance Survey. The entries are distributed by cash expenses as a fraction of rent revenues. The green dots are the fraction of operators in each bucket who have a mortgage. Panel B shows, for Invitation Homes, the change in same home operating expenditures per home in each market by the change in number of homes in each market when it merged with Starwood Waypoint Homes. The dotted black line indicates no change in operating expenditures per home.

Figure 4: Market-level occupancy and turnover for Invitation Homes

Panel A: Occupancy



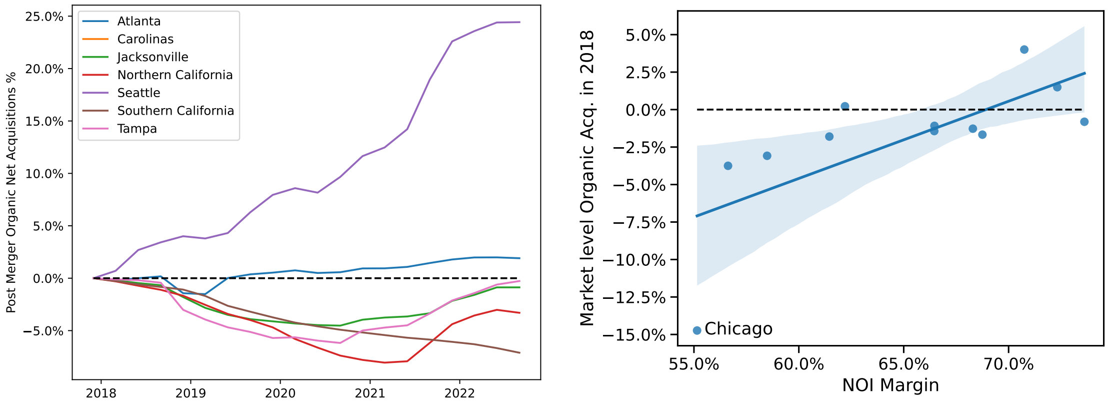
Panel B: Quarterly Turnover



Notes: This figure shows market-level occupancy and company-level turnover data from Invitation Homes' earnings statement supplements. Vertical lines on both panels show dates when the merger between INVH and SWH was announced, and when the merger was completed. INVH does not report market-level turnover.

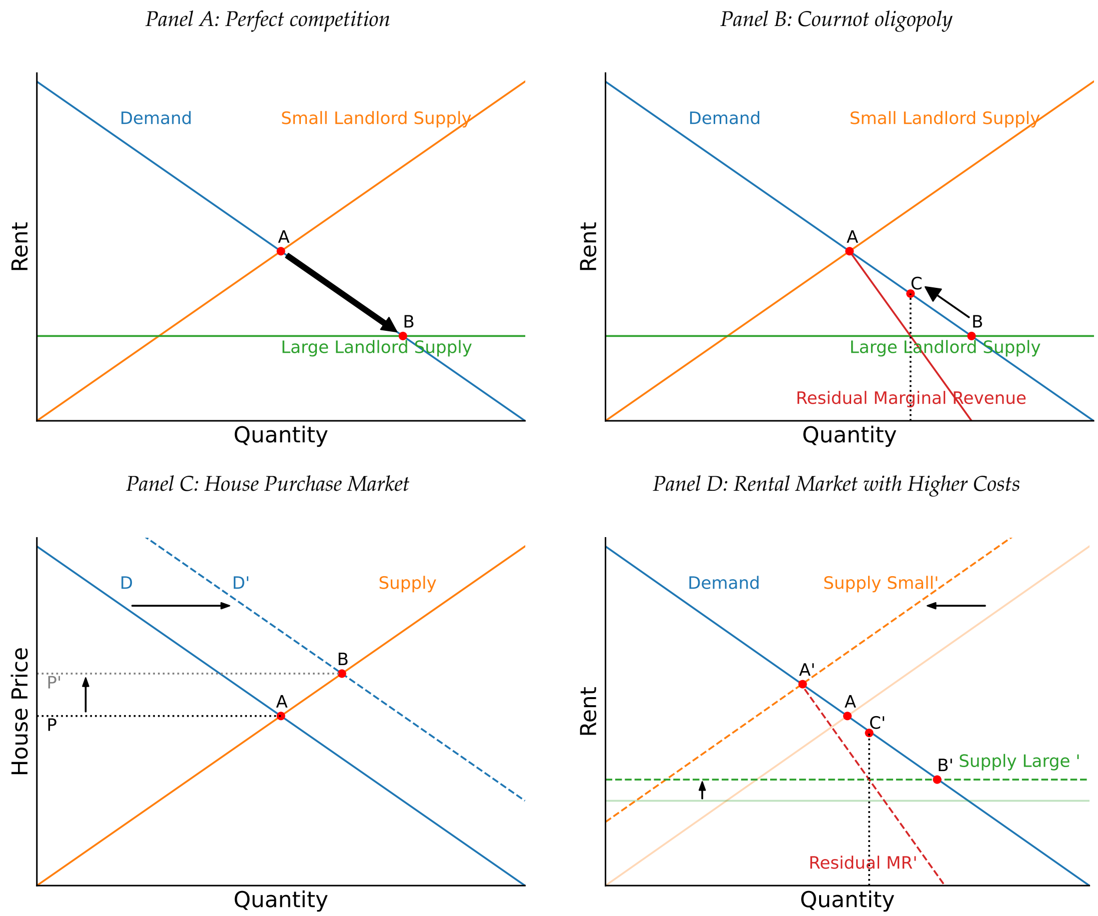
Figure 5: Organic growth by Invitation Homes

Panel A: Market-Level Cumulative Organic Growth Post Merger *Panel B: Post Merger Organic Growth and NOI Margins*



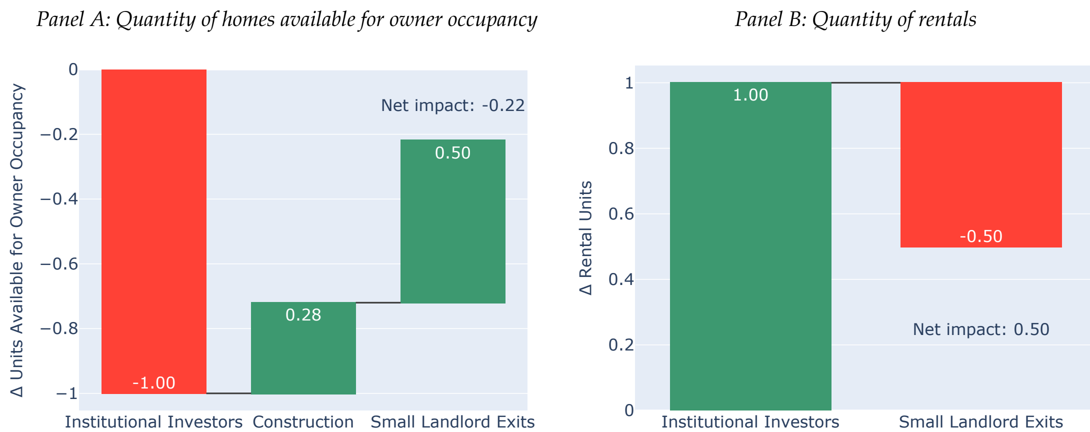
Notes: Data for both panels comes from earnings statement supplements for Invitation Homes. Panel A shows the cumulative organic growth in a subset of markets following the merger of INVH and SWH that was completed in November of 2017. Cumulative organic growth post merger is the net number of homes gained in each market in 2018 and onward, divided by the number of homes in the market at the start of 2018. Panel B shows the cumulative organic growth for 2018, the year after the merger, plotted against the net operating income (NOI) margin for each market.

Figure 6: Stylized example of large landlord entry



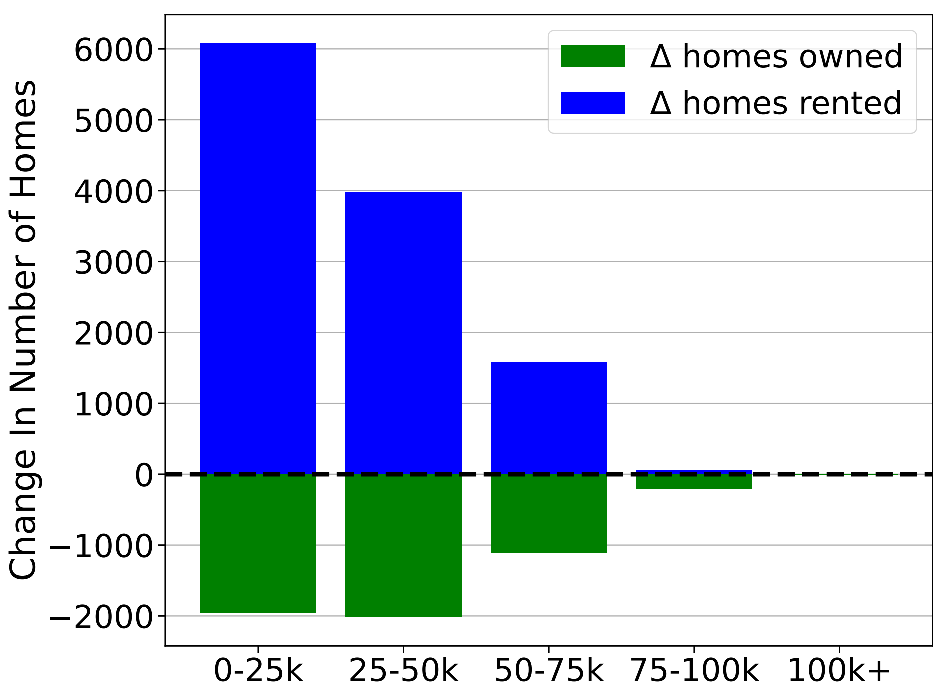
Notes: This figure shows a stylized model of supply and demand for single-family rentals. Households have downward-sloping demand and small landlords have upward-sloping supply. In Panel A, one large landlord with constant returns to scale enters and behaves competitively, which shifts the equilibrium from A to B. In Panel B, the large landlord chooses the profit maximizing quantity where residual marginal revenue intersects its cost curve, which shifts the equilibrium from B to C. Panel C shows the home purchase market. Large landlord demand for homes shifts the demand for owning homes to the right, raising prices, which raises small and large landlord costs. Panel D shows the effect of these higher costs in the rental market.ermin

Figure 7: Impact of institutional investors on homeownership and the rental supply



Notes: Panel A shows the change in housing available for owner occupancy due to a purchase of 1 unit by institutional investors. It shows the initial change from the purchase and then the construction response and the response of small landlords. Panel B shows the change in total rentals available due to the purchase of 1 housing unit by institutional investors. It shows the initial change from the purchase and then the response by small landlords.

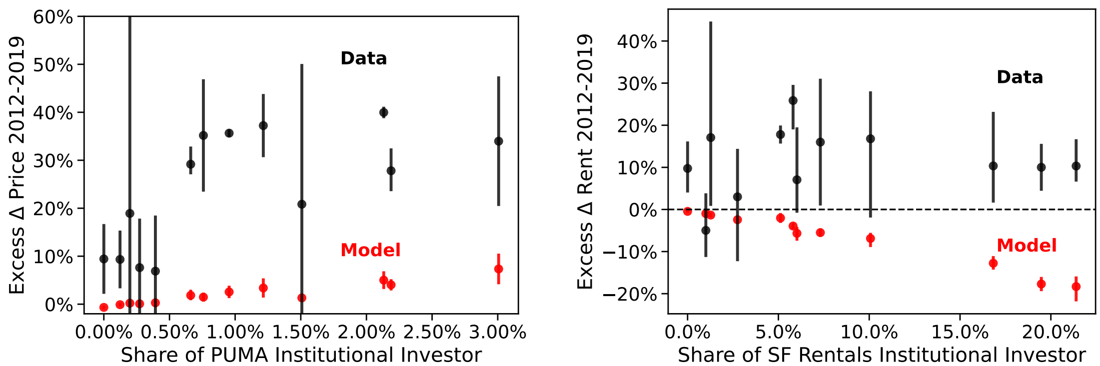
Figure 8: Loss in homes/gains in rentals upon institutional investor entry by income group



Notes: From the simulation of institutional investor entry in the housing market, this figures show how each groups' housing allocations change. The blue bars shows the number of rentals an income group gains. The blue bars show the number of owner-occupied homes an income group loses. They do not sum to the same number because builders build homes when institutional investors enter, and a group can move into or from the modeled outside asset, which consists of housing in PUMAs lacking data for some variables, housing with a median year built of 1939 or older, housing with low prices and rents, and housing outside of Georgia.

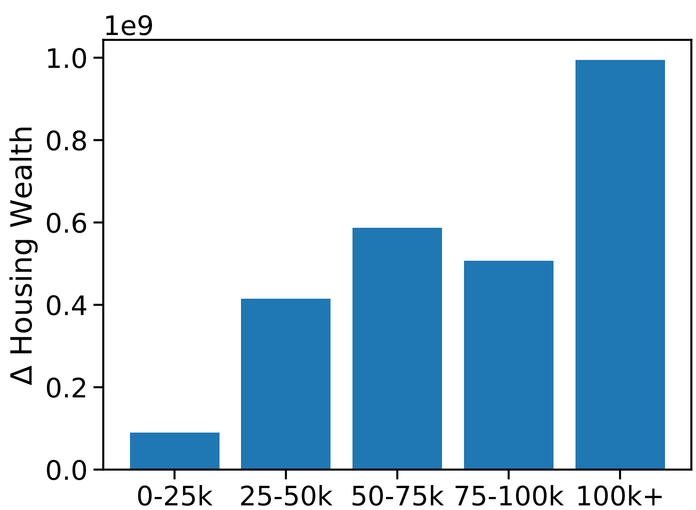
Figure 9: Price and rent changes upon institutional investors entry

Panel A: Prices *Panel B: Rents*



Notes: This figure shows the model-implied price and rent impacts of institutional investor entry into Georgia. The x-axis shows the share of the entire PUMA's housing stock or rental stock the investors own, and the y axis shows the excess increase in price or rent in comparison to the increase in the rest of the US. The black binscatter shows the data association from 2012 to 2019 of these investors with prices and rents. The red binscatter is the model output. Prices and rents come from the Census ACS1 data tables.

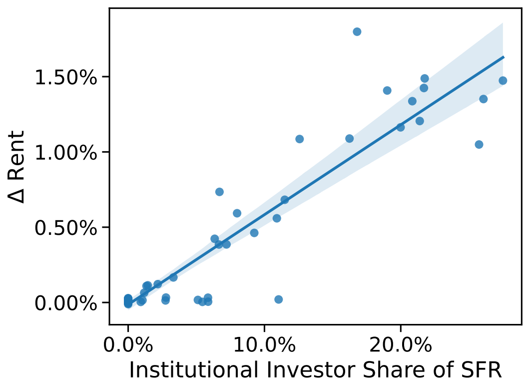
Figure 10: Institutional investor impact on housing wealth



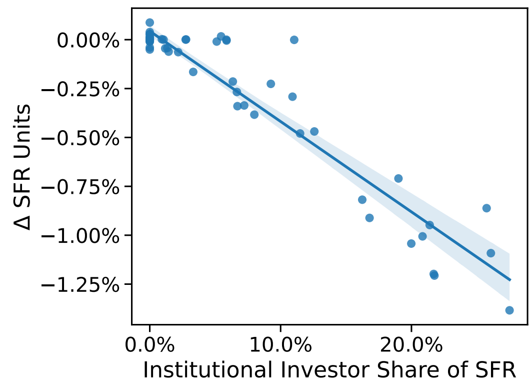
Notes: This figure shows the how many dollars an income group gains due to institutional investor entry as implied by the baseline model simulation.

Figure 11: Impact of a merger of large landlords

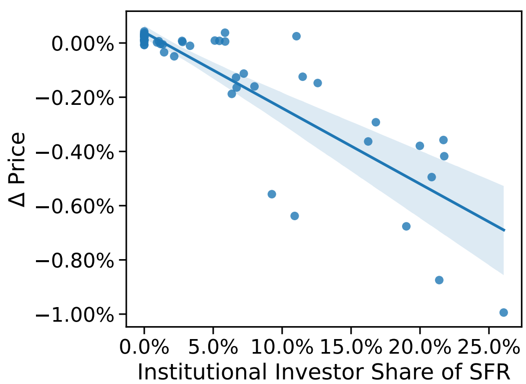
Panel A: Change in rents



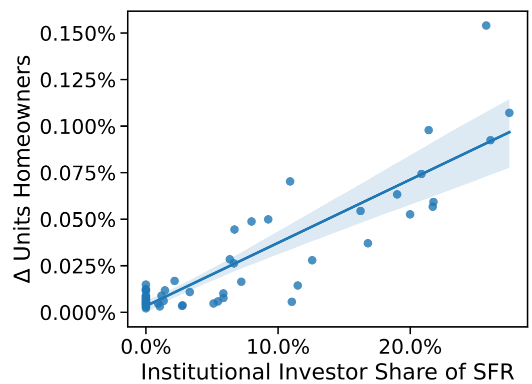
Panel B: Change in quantities



Panel C: Change in home prices

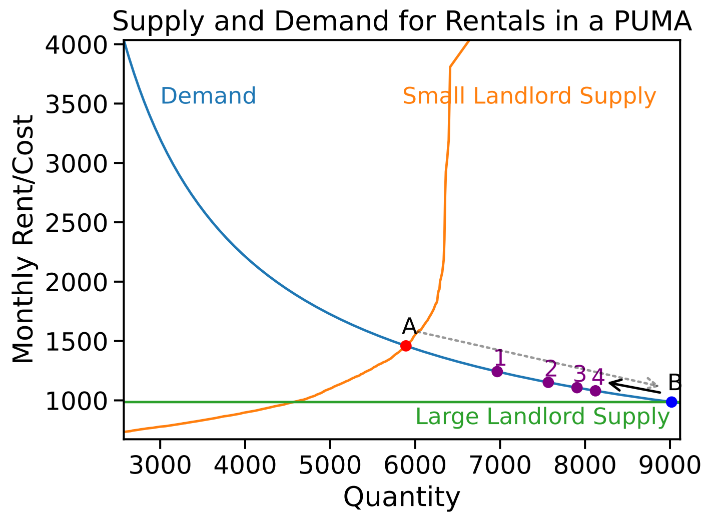


Panel D: Change in homes owned by households



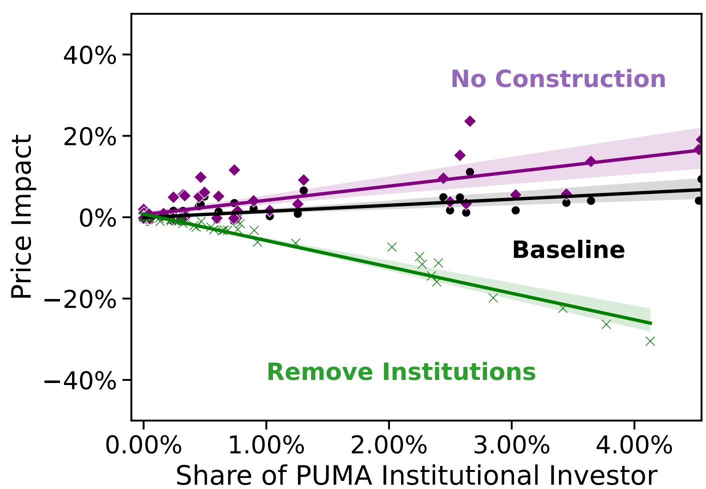
Notes: This figure shows the model-implied impact of a merger of two large landlords, with no adjustment costs. Panel A shows the change in single-family rents due to the merger in each PUMA, Panel B shows the change in the quantity of single-family rentals in each PUMA. Panel C shows the change in home prices in each PUMA, and Panel D shows the percentage change in homes owned in each PUMA. The x-axis is the institutional investor share of single-family rentals in a PUMA when 4 companies operate.

Figure 12: Stylized example of merger



Notes: This figure shows the equilibrium quantities and rents for one PUMA's single-family rental market when there are no large landlords (A), when there are either infinite landlords or the ones that exist choose competitive quantities (B), and then when there are 4, 3, 2, or 1 large landlords. A merger between 2 of 4 companies would be a move from (4) to (3).

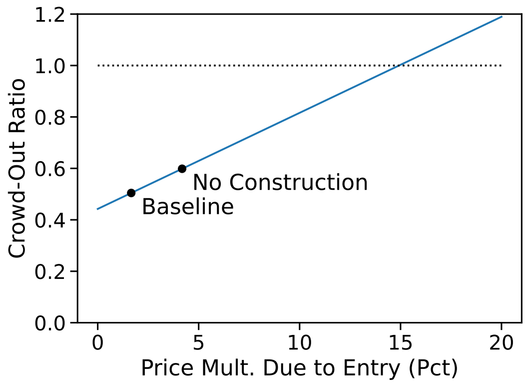
Figure 13: Price impact in counterfactual experiments



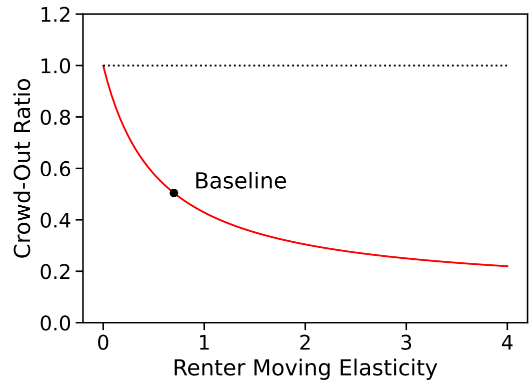
Notes: This figure shows the price impact in each census PUMA for the baseline estimation ("Baseline") where institutions enter the housing market, a counterfactual that consists of the baseline but no construction ("No Construction"), and a policy simulation where institutional investors are removed from their exact market footprint in 2019 and the housing market has to clear those now vacant units without adjustments by construction ("Remove Institutions").

Figure 14: Sensitivity of crowd-out ratio to parameters

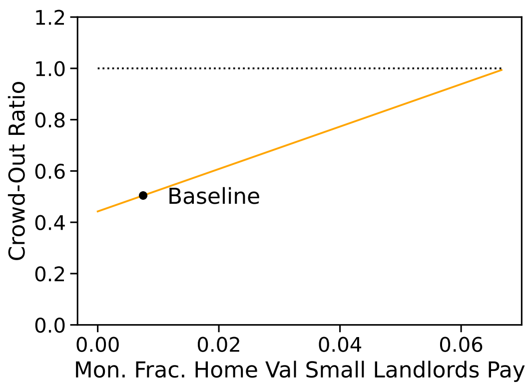
Panel A: Price Multiplier



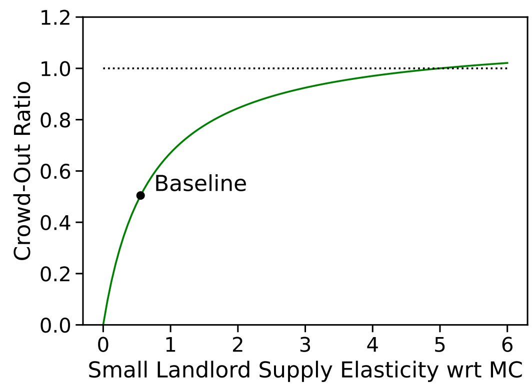
Panel B: Renter Elasticity



Panel C: Fraction of Price Paid By Small Landlords

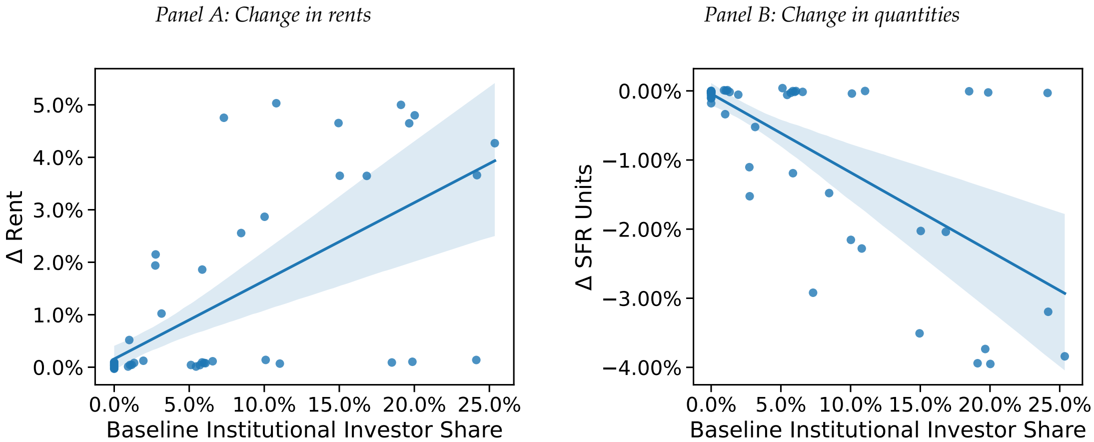


Panel D: Small Landlord Elasticity to MC



Notes: This figure shows how the crowd-out ratio varies with estimated parameters. Panel A shows the percentage increase in purchase prices due to institutional investors buying 1pp of the housing stock. It shows both the baseline value and the no construction value. Panel B shows how the ratio varies with the magnitude of the percentage change in rental quantity demanded for a 1pp increase in rents. Panel C shows how the ratio varies with the fraction of a home's value that small landlords pay each month in marginal costs, and includes cash costs and opportunity cost. Panel D shows how the ratio varies with the percentage change in small landlord quantity due to a 1pp increase in marginal costs.

Figure 15: Impact of a 5% cap on annual rent increases for large landlords



Notes: This figure shows the model-implied impact of a 5% cap on annual rent increases for large landlords. Panel A shows the change in single-family rents and Panel B the change in the quantity of single-family rentals in each PUMA. The x-axis is the institutional investor share of single-family rentals in a PUMA when there is no cap.

Table 1: Difference in census tract characteristics for movers into institutional investor–owned homes

	Mean Tract Difference
Δ Med. HH. Income	12.2%
Δ Math Scores	5.8%
Δ Jail Rate	-6.0%
Δ Top 20%-ile Income	3.4%

Note: This table shows the mean difference in percent between destination and origin census tract characteristics for those who moved into institutional investor properties for the first time between November 2018 and November 2019. The first row is the difference in median household income from the American Community Survey, the second row the difference in 2013 math test scores from Opportunity Insights, the third row is the difference in historical likelihood of incarceration from Opportunity Insights, and the final row the historical likelihood to get into in the top income quintile from Opportunity Insights.

Table 2: Previous-region variables on moving into an institutional investor rental

	log(med. income)	frac college	log(math scores)	log(jail)	log(inc. top quintile)
	(1)	(2)	(3)	(4)	(5)
new to institutional investor home	-0.011***	-0.010***	-0.010***	0.045***	-0.023***
New Tract FE	Y	Y	Y	Y	Y
Observations	591776	591776	591776	591776	591776

Note: *p<0.1; **p<0.05; ***p<0.01. The regression is at the individual mover level for all movers I observe in the US between November 2018 and November 2019, inclusive, who move into a census tract with institutional investor presence, who have census tract data. Clustering is at the new census tract level. The table compares, within a given new census tract, those who move into an institutional investor home for the first time and those who move into a non–institutional investor home or those who move into an institutional investor home who were in one previously. The outcome variables are the logs of the measures for the origin geography. The first column is the previous region's median household income from the American Community Survey 5-year tables. Column 2 is the previous region's fraction of residents with a college degree. Column 3 is the previous region's 3rd-grade math test scores from 2013. Columns 4–5 are outcomes of children from a given region, including the fraction of children from that region who become incarcerated and the fraction who enter the top income quintile. These represent historical mobility measures, not future outcomes. The outcome variables in columns 3–5 come from Opportunity Insights.

Appendix

A. Differences Between Small and Large Landlords

This section provides additional details on the differences between large and small landlords' operating costs. The main body of the paper already covers how institutional investors are much larger than the tiny, local operators, how small landlords appear to have decreasing returns to scale, and how large landlords have low average costs and appear to have constant returns to scale in operating costs over a large range of quantities.

Large landlords appear to have lower average costs than small landlords due to efficiencies highlighted by other research and by operators. Figure 2 Panel B compares cost components for average small landlords from the RHFS to cost components from earnings statements for INVH and AMH ("large average"). Institutional investors have lower property taxes as a share of rent. This may be because institutional investors are more likely to appeal their property tax assessment valuations, send the appeals in batches which implies economies of scale, and are more likely to succeed in these appeals, as documented in Austin (2022). Institutional investors also have lower operating expenditures. AMH's IPO filing mentions that it obtains quantity discounts for materials regularly used, including paint, flooring, and blinds. INVH's IPO filing mentions that it can obtain discounts for HVAC systems and contractor discounts by working directly with vendors on projects for which it does not use in-house staff. Large landlords have much lower insurance costs, at 1–2% of rent rather than 5–6%, which operators in the industry say is due to bargaining with insurers to get a bulk discount. Research from Kim et al. (2025) supports that large operators pay less in insurance using CMBS insurance cost data.

Institutional investors pay less for property management expenses, possibly due to vertical integration. While in Figure 2 Panel B it appears that large landlords pay more in management costs, that is because 83% of small landlords hire no professional management. When they do, they pay an average fee of 10% of rent. Institutional investors, on the other hand, have vertically integrated management companies and pay 4–7% of rent toward their internal management operations. Institutional investors also have vertically integrated leasing and acquisition teams. AMH, before internalizing its acquisition team, paid a 5% fee on top of all closing costs for each acquisition, which suggests that it may have saved some of this 5% by bringing this input in-house.

Large landlords have more debt and pay lower average interest rates than small landlords. Most small landlords do not have mortgages: In the RHFS, 63% of small landlords do not have mortgages or similar debt and in the Verisk data, 57% of small landlords do not have a mortgage. Institutional investors, on the other hand, are highly levered. In 2021, INVH had a debt-to-value ratio of 51% and AMH of 33%. Institutional investors use many types of debt, including asset-backed securitizations, bonds, term loans, and credit lines. I show differences in interest rates for existing and new small landlord mortgages, existing and new owner-occupied mortages, and the weighted average interest rates on debt for INVH and AMH in Figure B3. There is an interest rate spread between new mortgages for owner-occupants and small landlords of approximately 0.2%. The spread is larger for existing mortgages, at approximately 0.5%. AMH and INVH have significantly lower costs of debt than small landlords and owner occupants. INVH in particular has a lower cost of debt than AMH, possibly due to shorter term lengths. While a comparison of interest rates on identical loans is not possible, the data suggest that institutional investors use a number of debt instruments that small landlords and owner-occupied households do not, and are able to achieve lower interest rates than small landlords.

B. Market Power in single-family Rentals

A residential real estate company can lower quantities to raise rents in two ways: decreasing the number of units, or increasing vacancy. Determining which channel market power is expressed through has welfare implications because if companies with market power increase vacancy, that decreases the housing supply because no one can live in those units. But if they reduce quantities by selling homes or buying fewer homes, another landlord or a homeowner could purchase the homes, in which case the housing supply is decreased by less because others can live in these units.

Whether market power will be expressed in vacancies or sales depends on the liquidity of the real estate asset and on the time horizon of measurement, because holding a unit vacant is costly.

An operator who keeps units vacant does not receive revenue but still pays variable costs including property taxes, which make up around 20% of typical rent revenues, a portion of maintenance costs, and debt payments if the owner has debt. Therefore, an operator would be incentivized to sell excess vacant units if possible. The more liquid a real estate asset class is, the easier it would be to sell these units rather than carry them and incur variable costs. Single-family homes are relatively liquid real estate assets because one can sell individual units, and can sell to both landlords and homeowners. Other real estate asset classes, like multifamily homes, are less liquid because it is harder to sell a single unit in a large apartment building, and if you want to sell an entire multifamily property your exit liquidity is only other landlords or converting the entire building to a condominium or a co-op. So in single-family homes, we could expect market power to be expressed through selling off units or not buying them in the first place and in multifamily, we could expect market power to be expressed through increasing vacancies or not building the buildings originally. Additionally, the time horizon matters for how market power is expressed because in the long run, it is easier to adjust the number of units owned. Therefore, the importance of the units channel is likely to increase relative to the vacancy channel as the time horizon increases.

These tradeoffs are illustrated in the stylized model below. A firm chooses between either lowering its quantity of units, $\bar{q}$, or increasing its vacancies, v, to maximize profit, π. It earns rent, R, on occupied units, pays a marginal cost on occupied units, mc_o, a marginal cost on vacant units, mc_v, and pays adjustment costs for either selling a unit, $f(\bar{q} - q_i)$, or changing vacancies, $g(v - v_i)$:

$$\pi = R(\bar{q} - v) - mc_o(\bar{q} - v) - mc_v v - f(\bar{q} - \bar{q}_i) - g(v - v_i). \tag{30}$$

The derivatives with respect to decreasing both total units and occupancy are below:

$$\frac{\partial \pi}{\partial(-\bar{q})} = \frac{\partial R}{\partial(-\bar{q})}(\bar{q} - v) - R + mc_o - f'(\bar{q} - \bar{q}_i), \tag{31}$$

$$\frac{\partial \pi}{\partial v} = \frac{\partial R}{\partial v}(\bar{q} - v) - R + (mc_o - mc_v) - g'(v - v_i). \tag{32}$$

For both adjustments, the first term is the increase revenue due to higher rents from lowering the rental supply. When a unit is sold, if it goes to a landlord it does not decrease the rental supply, but if it goes to an owner occupant it decreases the rental supply by 1. Either sale would affect equilibrium rents and prices, so the final change in quantity would be between 0 and 1. For decreasing quantities through rents to work at all, there must be partial segmentation in the market: The sold unit must exit the rental market at least some of the time. The second term is the decrease in revenue by having one fewer rent earning unit. The third term is the change in marginal cost by having one fewer occupied unit and in the second case, one fewer occupied unit and one more vacant unit. The fourth term is the adjustment cost in each scenario. I compare the changes in profits due to each channel by taking the difference, and I assume that adjustment costs with respect to increasing vacancies are negligible:

$$\frac{\partial \pi}{\partial(-\bar{q})} - \frac{\partial \pi}{\partial v} = (\frac{\partial R}{\partial(-\bar{q})} - \frac{\partial R}{\partial v})(\bar{q} - v) + mc_v - f'(\bar{q} - \bar{q}_i). \tag{33}$$

The first term depends on the difference in the impact on equilibrium rents of decreasing units by 1 compared to increasing vacancies by 1. Increasing vacancies lowers the rental supply by 1 before accounting for equilibrium effects. Decreasing the number of units lowers the rental supply by 1 if selling to an owner occupant or 0 if selling to a landlord, therefore the first term is likely to be negative. In single-family homes, this term is likely closer to 0 than in multifamily, all else held constant, because a larger portion of single-family housing demand comes from those intending to occupy the unit rather than rent it out. The second term is the marginal cost of holding a unit vacant. This is likely to be similar to the cost of holding an occupied unit since many costs for landlords, including property taxes, insurance, debt payments, and some amount of maintenance and repairs do not depend on whether a unit is occupied. The third term is the adjustment cost of selling a unit. It's easier to decrease one's portfolio size in single-family rentals where one can sell units one by one, rather than in multifamily rentals where one has to sell units in the same property at the same time. Additionally, exit liquidity can come from either households or landlords, rather than multifamily where exit liquidity is more likely to come from landlords. If $mc_v > f'(\bar{q} - \bar{q}_i)$, then a firm is more likely to decrease units rather than vacancies.

Therefore, for this unit channel of market power to be relevant (after the unit has already been created), we need segmented markets where a sold unit could exit one's sub-market, high vacancy costs relative to adjustment costs, and no benefit from destroying the product. This is most likely to be present in markets with large, expensive durable goods, that are undifferentiated enough that they can be used in multiple market segments, where marginal costs of vacancy do not differ largely from marginal costs when in use, with liquid secondary markets.

I examine whether market power is more likely to be expressed through adjusting the number of units or vacancy by first examining trends at the market level for INVH with data from its earnings statement supplements in Figure 4 Panel A. Occupancy rates fluctuate here by up to 4 percentage points (pp) from 95% to 99%. They increased sharply after the onset of the COVID-19 pandemic, which is consistent with the migration of people out of cities as documented in Gupta, Mittal, Peeters and Van Nieuwerburgh (2022) and Coven, Gupta and Yao (2023). Occupancy did not change a noticeable amount around the date of INVH's merger with SWH. Panel B shows that company-level quarterly turnover does not appear to change due to the merger and instead follows a consistent downward trend. INVH does not report market-level turnover. High occupancy rates and low turnover that move due to trends unrelated to a large merger suggest that the mechanism through which market power is expressed is not increasing vacancies or turnover to raise rents.

Institutional investors appear to adjust their number of units strategically to maximize profits. I examine INVH's market-level organic growth in Figure 5. Panel A shows market-level cumulative organic growth in each quarter following the merger with SWH. Changes in the number of units are at larger magnitudes than occupancy changes at the market level. In a number of markets, INVH decreased the quantity of homes owned after the merger by up to 7.5%. In Seattle, INVH increased its portfolio size organically by 25%. Panel B shows the relationship between the cumulative net organic growth and net operating income margins in each market in the year after INVH's merger with SWH. INVH adds homes organically in markets where operating margins are high, and decreases homes in markets where operating margins are low. The adjustment in number of units based on net operating margins is consistent with profit maximization, therefore suggesting that changes in units may be the strategic variable of choice for institutional investors. I run a horse-race regression at the market level to compare how changes in occupancy and changes in the number of units vary with the number of units gained in the merger of INVH and SWH. I first examine the results graphically in Figure B6. Changes in the number of units are an order of magnitude larger than changes in occupancy, and are mostly negative, suggesting that INVH was more likely to decrease quantities rather than occupancy due to the merger. I then examine this specification in a regression in Table B4. Column (1) shows the regression on the net acquisitions in a market in the year following the merger, Column (2) shows the change in occupancy in the year following the merger, and Column (3) shows the change in yearly net acquisitions in each market. While there are too few markets to get significant results from these regression, coefficient sizes are larger for quantity changes than occupancy and show some trend with respect to the number of units gained in the merger, after controlling for net operating income margins.

To explore whether institutional investors express market power by decreasing their number of units, I examine how INVH changed quantities at a granular level following its merger with SWH in November of 2017. With all else held constant, one would expect the quantity decrease due to a merger of Cournot oligopolists to depend on where the new residual marginal revenue curve intersects with the merged entity's supply curve, relative to the original entities' residual marginal revenue curves. First, one would expect this change to be largest for similar sized large entities merging, but not entities with large differences in sizes. For example, if two entities merged and one had substantial presence in a tract and the other had none, we could expect zero change. However, if both had substantial presence, the merged entity would gain a large amount of the residual demand. Second, one would expect this change to be largest in regions with inelastic demand for rentals. And third, one would expect this change to be largest where there is the least competition from non-merging entities.

I examine quantity changes with respect to this first margin at the census tract level by plotting how many units the combined INVH and SWH entity sold from November 2017 to November 2018 as a function of the number of units each entity had in November 2017 at the time of the merger. I focus on Atlanta where I am able to identify 99% of the units the combined entity had at the end of 2017 and 98% at the end of 2018, and where there was substantial presence by both companies in the merger. I plot the average percentage of units sold in a given census tract as a function of the number of units in a census tract held by both INVH and SWH in Figure B7. Panel A shows averages of census tracts for each section of the quantity space. Panel B shows these averages after removing county level means to control for unobservables at the county level, including, for example, county level NOI margins. I find that where both companies had substantial presence, the combined entity sold on average a large percentage of its units, which is consistent with where a merger would result in the largest gain in market power. In census tracts where

INVH and SWH had 20 or more units before the merger, the combined entity sold a total of 4.0% of its units in the year after the merger. In all other census tracts in Atlanta, the combined entity sold a total of 2.2% of its portfolio. These results suggest that a gain in market power due to a merger may lead to sales of units, however this effect is not monotonically increasing along the 45 degree line.

While I do not have occupancy data at this level of granularity, the lack of changes in occupancy at the market level and the large changes in quantities at the market level support that the margin of adjustment for profit maximization in single-family rentals is changes in the number of units. It is possible that the implication of gains in market power due to a merger was of second order importance relative to NOI margins for the company's quantity adjustment strategy, and therefore mergers wouldn't result in observable decreases in quantities.

Profit maximization through the adjustment of units rather than occupancy is consistent with models of Cournot oligopoly (Cournot, 1838), and with capacity constraints followed by Bertrand competition, as modeled in Kreps and Scheinkman (1983), where equilibrium quantities are the Cournot quantities. Bertrand competition (Bertrand, 1883) would be applicable if the companies chose rents and then the market set quantities, which would result in market power expressed through vacancies. This expression of market power has important welfare implications because when units are sold, others can occupy the units, therefore market power expressed by selling units decreases the housing supply by less than market power expressed by increasing vacancies.

C. Data Appendix

C.1 Property Sample

To construct the Verisk property sample, I first keep only the properties that have a property indicator for single-family residence, townhouse, apartment, condominium, duplex, triplex, or quadplex. I then exclude properties with no street information, mobile homes, and any remaining properties with duplicate address indicators. I classify properties as owner-occupied if they have an owner-occupied flag of O or S, or rental if they have a flag of A, T, or null.

There are multiple reasons why the sample undercounts rental units. It is possible that units in Verisk that are rented out used to be owned and their owner-occupancy codes were not updated.

Table A1: Comparison of Verisk housing units by ZIP code to census units

	Total Units	Owner-Occupied	Rental Units
Units	1.064***		
	(0.001)		
Owner-Occupied Units		0.991***	
		(0.001)	
Non-Owner-Occupied Units			1.086***
			(0.004)
Observations	32,456	32,456	32,456
R^2	0.940	0.962	0.744

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the results of regressions of American Community Survey 5-year (ACS5) housing units from 2020 (includes all of 2020) on Verisk housing units for February 2021. The first column is all units, the second is owner-occupied units, and the third is rental units.

In addition, for multiunit apartment buildings, Verisk sometimes has one row for each apartment in the building and other times has one row for the entire apartment. Sometimes there are multiple rows for apartments within a building but each row has the total building's number of units. To address this, I identify any row where the value of the address, either assessed or market, divided by the number of units, is less than 50 thousand. For these rows, I change the number of units to 1. I also change to 1 the apartment number of any row that has a living square footage per unit of less than 100.

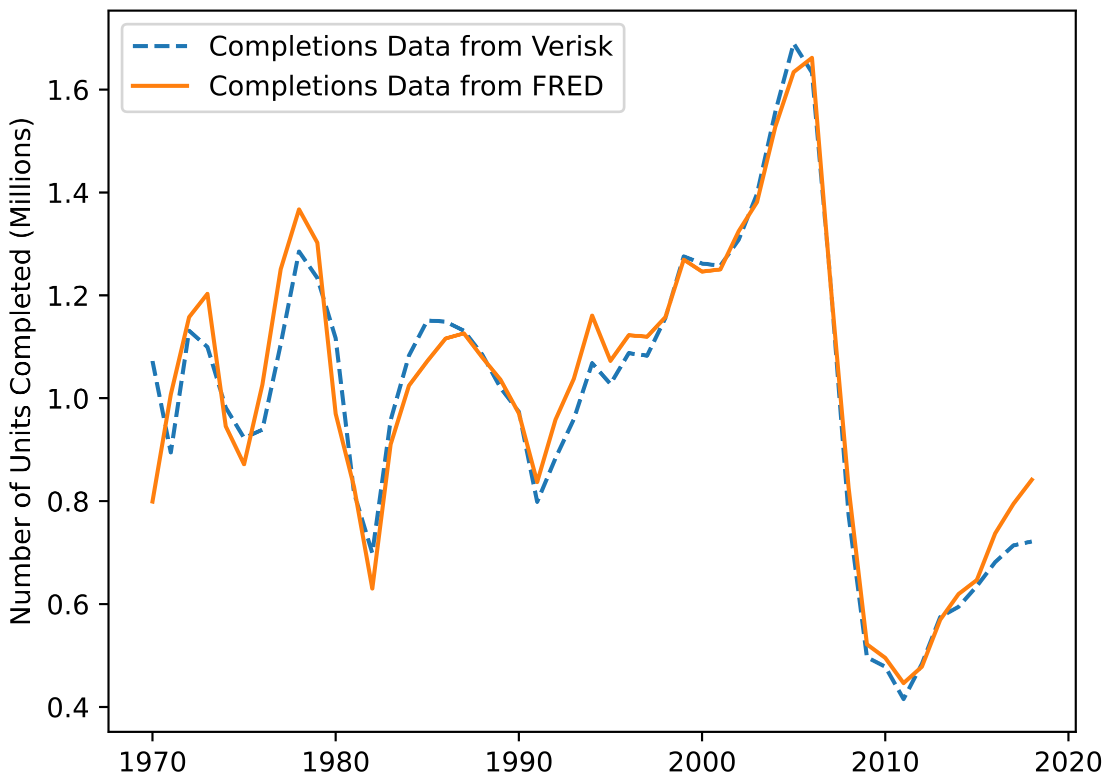
I validate the number of institutional investor–owned homes that I am able to identify for each public company in the table below. The identification is described in the data section of the paper.

Table A2: Verisk number of units compared to public information

	Data	Target	Percentage
Invitation Homes	73066	80177	91%
American Homes For Rent	47699	53584	89%
Tricon	19630	22766	86%

Note: This table shows a comparison of the number of units belonging to each company identified with Verisk data with information available in Securities and Exchange Commission (SEC) filings for 2020Q4.

Figure A1: Supply validation



Note: This plot shows the aggregate number of housing completions for the US each year from Verisk, where the completion date is set to the year the property was built, for comparison with aggregate US completions for single-family homes from Federal Reserve Economic Data (FRED).

C.2 Mover Sample

To construct the Verisk moving sample, I first clean the property dataframe for 2019 as described above. I then take the Verisk moving history and exclude anyone with a deceased flag of Y or null. I use an anonymized dataset, so I cannot drop duplicate address histories using names or similar names. Instead, I drop all address histories that are identical. This is possibly an over-correction, as different people with the same address history would be dropped. I then reshape the moving data from wide to long to obtain the dataset at the person ID×address× previous address level, with the date recorded at the previous address and date recorded at the current address. I drop those with null ZIP codes, true duplicates, and duplicates.

At this stage, there are many duplicate PID× EFFDATEs. I want to identify one address at a given date for a given person. Of the duplicates at the PID× EFFDATE level, I drop those that do not merge to a property identifier from the cleaned property dataframe. Of the remaining duplicates, I rank them based on their postal delivery designation in the following order: street or residential, rural route, general delivery, high rise or business, PO box, null, firm or company address and keep the duplicate that has the first rank in that order. Finally, I drop all entries that have remaining duplicates and do not select one of the duplicates to keep.

From these cleaned data, I create two types of datasets. One is the sum of all moves between census PUMAs and asset classes (owner-occupied, single-family rental, and multifamily rental) from 2012 to 2019. I use this dataset for the estimation of migration costs. The other dataset examines moves in a given year to see where people who move into institutional investor homes come from. I create a window such that those who moved before the start of the window are considered residents of their most recent location and those who moved during the window are considered movers from their previous location to their new one. Those who move after the window are not considered movers. After creating a moving window, I clean and merge the property datasets from the start and the end of the window to get start of window and end of window attributes, including the owner at each point. This allows me to observe where people moved from and where they moved to. In the main analyses with this data, I examine only the identified movers, not those who did not move. I validate ZIP code and county level moves in the cleaned Verisk migration dataset for 2019 with USPS moves in 2019 to validate inflows and outflows in Appendix Table A3, and ACS moves from 2019 to validate exact region to region flows in Appendix Table A4. The migration dataset is highly correlated with both types of flows.

C.3 Landlord Costs

To construct a dataset of small landlords' single-family rental cost components, I start with the RHFS's publicly available data for 2018 and 2021. I filter the dataset by first keeping only 1-unit properties and then only "individual" type owners, which excludes corporations, REITs, and LLCs. For 2021, I exclude townhouses (for 2018, this field does not exist). I exclude assisted living homes and rent control homes, keep only homes with lease lengths of 1 year, and keep homes with

Table A3: Mover-level validation: Moves to and moves from a ZIP code

	Moved From Zipcode (USPS)	Moved To Zipcode (USPS)
Moved From Zipcode (Infutor)	3.239***	
	(0.002)	
Moved To Zipcode (Infutor)		2.944***
		(0.002)
Observations	291,168	291,168
R^2	0.867	0.872

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows regression results of Verisk moves on United States Postal Service (USPS) ZIP code moves. The first column shows results comparing moves out of a ZIP code in both datasets. The second column shows results comparing moves into a ZIP code in both datasets.

Table A4: Mover-level validation: County-to-county moves

	Moved From County 1 to 2 (ACS)
Moved From County 1 to 2 (Infutor)	1.622***
	(0.002)
Observations	426,676
R^2	0.703

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the regression results of Verisk county-to-county moves on Census county-to-county moves.

rent and market value both greater than 0. This results in a dataset of 601 individual landlords of 1-unit properties.

For the descriptive analysis, I use property tax and mortgage data from the RHFS, and for the model calibration, I use region-specific property tax and mortgage data from Verisk. The RHFS property tax data are bucketed; the buckets are the same for both the 2018 and 2021 samples. I use the midpoint of each bucket as the dollar amount of property taxes paid for the descriptive analysis. Some landlords in the RHFS report having a mortgage in the field for mortgages or similar debt but do not report an amount for this debt. For these landlords, I impute a mortgage balance outstanding as a fraction of market value based on the mean fraction for each bucket of property purchase years. As shown in Figure B4, small landlords appear to pay off their mortgages over time and appear to mostly have 30-year mortgages. For the descriptive analysis, I want to calculate interest expenses each year as a fraction of rent, assuming that their mortgages are paid off over time. I take the present value of the expected interest payments if the landlords pay off 1/30th of their mortgage each year and then turn this into a perpetuity equivalent to obtain a per-year interest expense. I use a discount rate of 5%, which is close to the CAPM value of 5.2%, as discussed in the small landlord estimation section. I use the median small landlord mortgage interest rate from Verisk, which is 5.25%.

There is significant heterogeneity in small landlord operating costs. Ideally, I could use a cross section of small landlord average operating cost components to describe this heterogeneity. Instead, the survey provides a snapshot and therefore contains year-to-year variability, as well. The dataset has separate columns for capital expenditures in each category and operating expenditures in each category. Except for when I reference recurring capital expenditures, all costs come from the operating expenditure columns. I average components of operating costs as a fraction of rent across landlords that are likely to be highly variable from year to year: recurring capex, repairs, and electricity and gas. I winsorize at the 5% level payroll expenses, water and sewer expenses, and uncategorized opex. The dataset does not distinguish between recurring capex and value-added capex. To obtain the recurring capex, I sum categories of capex that are likely to be recurring and exclude others that are less likely to be recurring. Recurring capex includes columns for the cost of access for people with disabilities, door upgrades, electrical system upgrades, roof upgrades, HVAC upgrades, plumbing upgrades, and window upgrades. I exclude exterior upgrades, other improvement costs, kitchen facility upgrades, carpet and floor upgrades, and bathroom upgrades.

To construct large landlords' AFFO, I add same-store operating expenses, same-store recurring capital expenditures, and company-level cash expenses including interest expense, management expense, and general and administrative expenses. I divide these by revenue to obtain AFFO as a fraction of revenue. For the descriptive analysis of cost components, I use data from FY2017 and FY2020 for comparison with the RHFS.

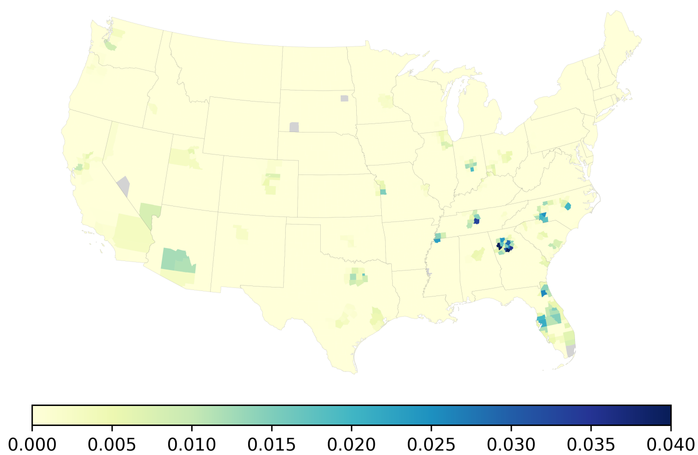
C.4 Geographic Crosswalks

To convert ZIP code level topography data from Lutz and Sand (2022) to the census PUMA level, I take centroids for each census tract in the US and then create a 3-mile circle and a 3–10 mile ring around them. I do a geospatial join of this circle and ring to a ZIP code–level map of land unavailability characteristics. This yields the average land unavailability within 3 miles of each census tract and 3–10 miles from the center of each census tract. I average this measure up to the PUMA level, which yields the average land unavailability for each house in the PUMA within 3 miles and within a 3–10 mile ring around it.

ZIP code–MSA (metropolitan statistical area) crosswalks come from the US Department of Housing and Urban Development (HUD). ZIP code geographies come from the Census TIGER-web files. To make county-level maps, I use a ZIP code–county crosswalk from HUD. I aggregate these ZIP code characteristics to the PUMA level for the demand estimation.

D. Additional Figures and Tables

Figure B1: Fraction of housing owned by institutional investors in February 2021



Note: For the US in February 2021, I show the fraction of the total housing stock that 7 institutional investors combined owned at the county level. These 7 are Invitation Homes, American Homes for Rent, Tricon Residential (now owned by Blackstone), Progress Residential, FirstKey Homes, Main Street Renewal, and Home Partners of America. Total housing stock comes from the Verisk data. Institutional investors' holdings are identified from tax addresses in the Verisk data.

Table B1: Institutional investor market presence

	Dependent variable: Institutional Investor Presence	
	(1)	(2)
log(Price)	-0.366***	-0.161**
log(Rent MF)	0.057	0.259***
log(Rent SF)	0.388***	0.308***
ΔPrice 06–12	0.011	-0.135*
ΔPopulation 06–12	0.491***	0.345**
Avg. Annual Job Growth 04–13	1.143**	1.118**
ΔPrice 10–12	-0.014	0.072
ΔRent 10–12	0.009	0.046
Foreclosures per Person	4.636***	4.317***
Dist. To Nearest MSA	0.005**	0.003*
Dist. To Nearest MSA Sq	-0.000**	-0.000*
log(Med. HH Income)	0.077	0.319***
Frac. White	-0.359***	-0.278***
Frac. College Edu	-0.604***	-1.205***
Middle School Math Scores 2013	0.130***	0.024
Housing Stock Controls	Y	Y
Weather Controls	Y	Y
Other Amenity Controls	Y	Y
Fixed Effects		State
Within R-squared	0.349	0.256
Observations	1555	1555

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the results of a descriptive regression at the PUMA level. The dependent variable is an indicator variable for PUMAs in which the institutional investors, combined, have 10 or more properties in the PUMA. Column 1 has no fixed effects, and column 2 has state-level fixed effects. Prices and rents are median values from the Census American Community Survey 1-year (ACS1) tables for 2012. "MF" is multifamily, and "SF" is single-family. Prices and population counts for 2006 are from the 2006 Census ACS1 at the PUMA level. I use a crosswalk from 2000 PUMAs to 2010 PUMAs from the Missouri Census Data Center so that I can compare values from 2006 to 2012. Average annual job growth from 2004 to 2013 and middle-school math scores from 2013 come from Opportunity Insights at the census tract level; I aggregate these to the PUMA level. Foreclosures per 2012 population come from foreclosure data from Zillow's ZTRAX and population data from the 2012 census. A PUMA's distance to nearest MSA comes from the distance of each ZIP code in a PUMA to the center of the nearest MSA; I then aggregate these distances to obtain the average at the PUMA level. Housing stock controls are the median year built of the owner-occupied housing, the median number of bedrooms of the owner-occupied housing, and the fraction of housing in a PUMA that is single-family. Weather controls are January temperature and sunlight and July temperature and humidity. Other amenity controls come from the 2012 Census ACS1 tables and are the fraction of the high-school-age population enrolled in high school, the fraction of the high-school-age population enrolled in private school, and the fraction of the total population with a commute shorter than 45 minutes.

Table B2: Within-ZIP-code-within-single-family differences in housing characteristics

	Rentals Not Institutional	Rentals Institutional	Owner Occupied
avg year built	1990.65	1996.09	1993.66
avg living sqft	1990.52	1890.24	2121.07
avg num. beds	3.25	3.39	3.41
avg num. baths	2.30	2.38	2.47
frac. single family	0.98	1.00	0.99

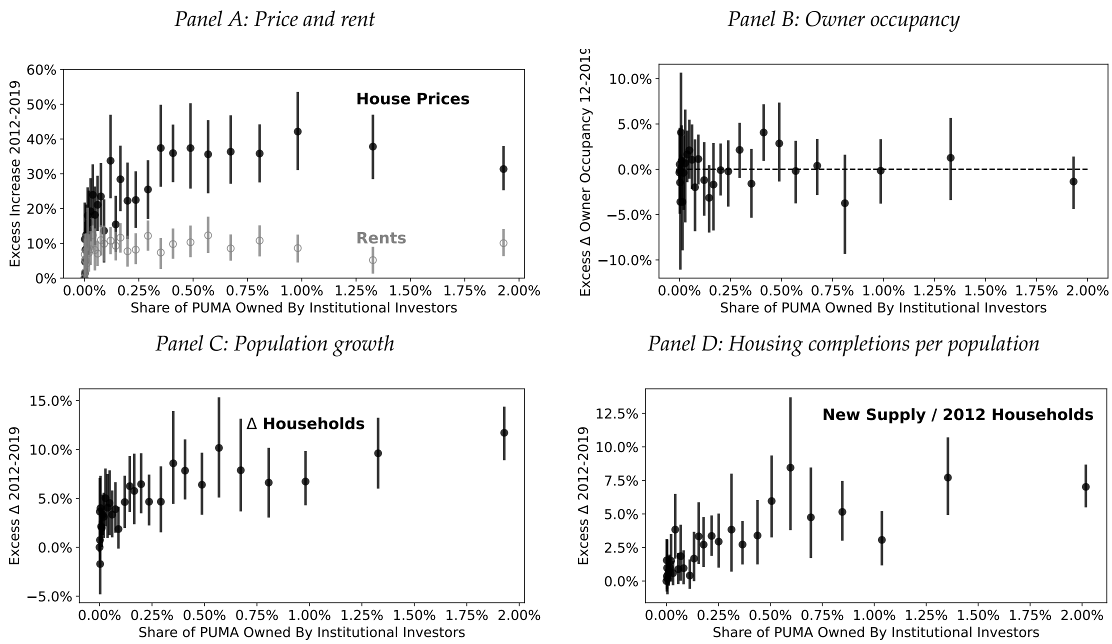
Note: From Verisk property data, I identify institutional investor holdings and compare their physical features in a given ZIP code with the features of the rest of the rental stock and of owner-occupied homes. I take these within-ZIP-code differences for ZIP-codes where more than 95% of the rental stock is single-family and compute a weighted average, weighted by the number of units institutional investors own in a given ZIP code. This results in a weighted average within-ZIP-code-within-single-family difference in the physical characteristics of institutional investor homes and other types of homes.

Table B3: Within-ZIP-code differences in housing characteristics

	Rentals Not Institutional	Rentals Institutional	Owner Occupied
avg year built	1985.54	1993.02	1988.93
avg living sqft	1831.05	1834.59	1984.85
avg num. beds	3.13	3.36	3.30
avg num. baths	2.26	2.42	2.43
frac. single family	0.79	0.99	0.91

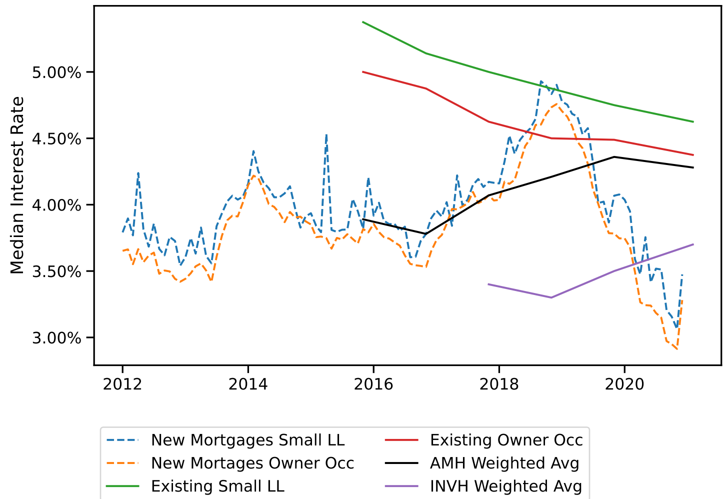
Note: From Verisk property data, I identify institutional investor holdings and compare their physical features in a given ZIP code with the features of the rest of the rental stock and of owner-occupied homes. I take these within-ZIP-code differences and compute a weighted average, weighted by the number of units institutional investors own in a given ZIP code. This results in a weighted average within-ZIP-code difference in the physical characteristics of institutional investor homes and other types of homes.

Figure B2: Associations with institutional investor share of housing stock



Notes: This figure shows binscatters of different PUMA-level variables on the fraction of the housing stock owned by institutional investors. PUMAs with no institutional investor presence are the intercept, so each plot shows the excess for the variable relative to the value for the rest of the country. Panel A shows changes in prices and rents relative to the rest of the US, where prices and rents come from the ACS1. Panel B is the change in the fraction owner-occupied from 2012 to 2019 from the ACS1. Panel C is the change in the number of households from 2012 to 2019. Panel D is the amount of new construction from 2012 to 2019 divided by the number of households present in 2012. The new construction counts come from the Verisk property files.

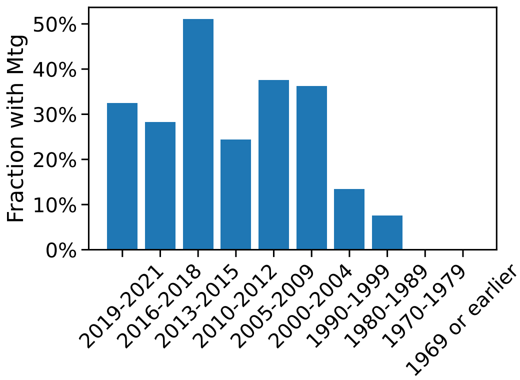
Figure B3: Cost of debt



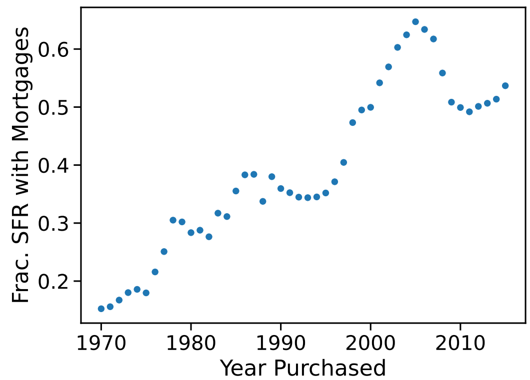
Note: This figure shows median interest rates for new mortgages for small landlords, new mortgages for owner-occupied homes, all existing mortgages for small landlords, all existing mortgages for owner-occupants, American Homes for Rent's debt, and Invitation Homes' debt. Data for the small landlords and owner-occupants come from Verisk. Data for American Homes for Rent and Invitation Homes come from earnings statement supplements. The time series is limited for existing mortgages because I have snapshots of the data starting from November 2015 until February 2021. For Invitation Homes, the time series is limited to after its IPO date.

Figure B4: Small landlord mortgages

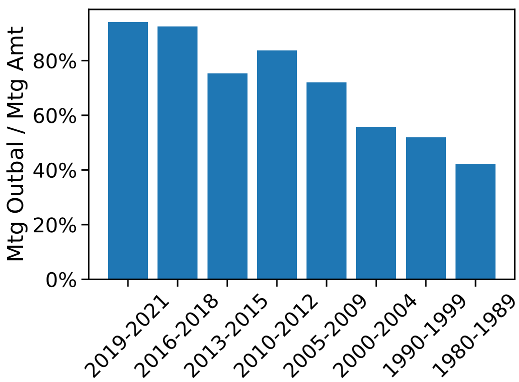
Panel A: Fraction of small landlords with mortgage by purchase date (RHFS)



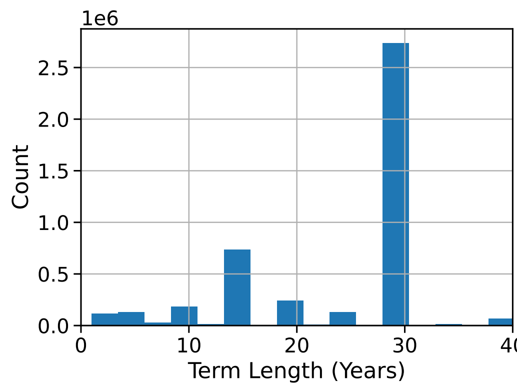
Panel B: Fraction of small landlords with mortgage by purchase date (Infutor)



Panel C: Mortgage % remaining

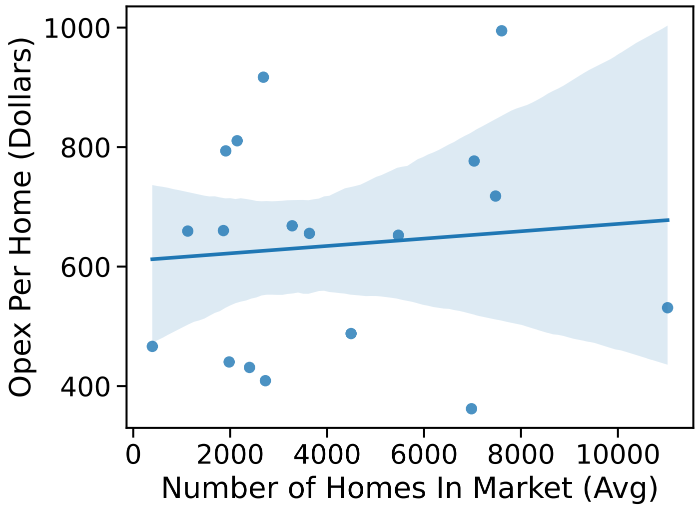


Panel D: Small landlord term length distribution



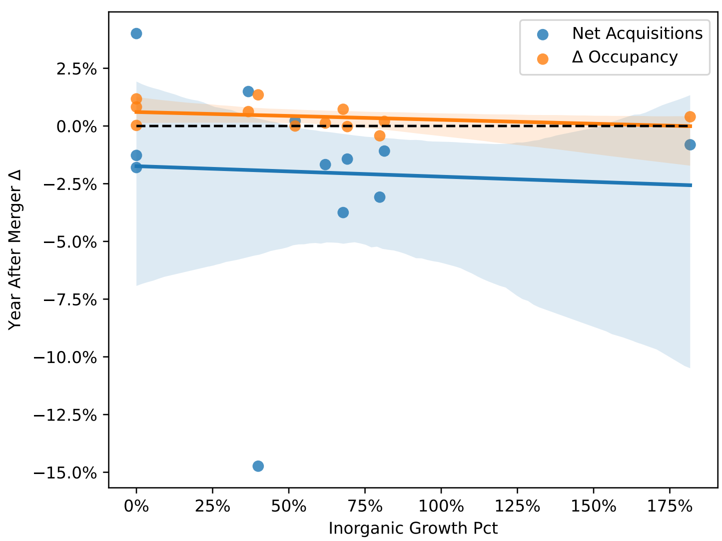
Note: Panel A shows the fraction of small landlords in a bucket who have a mortgage in the 2021 sample of the Rental Housing Finance Survey, where each bucket is a purchase date grouping. Panel B shows the fraction of small landlords with a mortgage by purchase year with data from Verisk. Panel C shows the fraction of the original mortgage balance remaining for each purchase year bucket for those who still have mortgages from the RHFS. Panel D shows the distribution of small landlord term lengths from the Verisk data. Two-thirds of the small landlords with mortgages in the Verisk data have term length information. I show the distribution from the data cross section from November 2015.

Figure B5: INVH market average opex per home



Note: This figure shows Invitation Homes' market-level average operating expenditures per home by the number of homes in each market. Data on operating expenditures by market come from Invitation Homes' quarterly earnings statement supplements.

Figure B6: Market-level net organic acquisitions and change in occupancy for INVH after merger



Note: This figure shows the market-level net organic acquisitions and the market-level change in occupancy for Invitation Homes in the year after they merged with Starwood Waypoint Homes, 2018. Occupancy compares the 2017 market average to the 2018 market average. Net organic acquisition in each market shows the number of homes gained in 2018, not due to a merger, divided by the number of homes in each market at the start of 2018. Inorganic growth percentage is the percentage increase in market size of INVH due to the merger with SWH. Data for this graph come from earnings statement supplements for INVH.

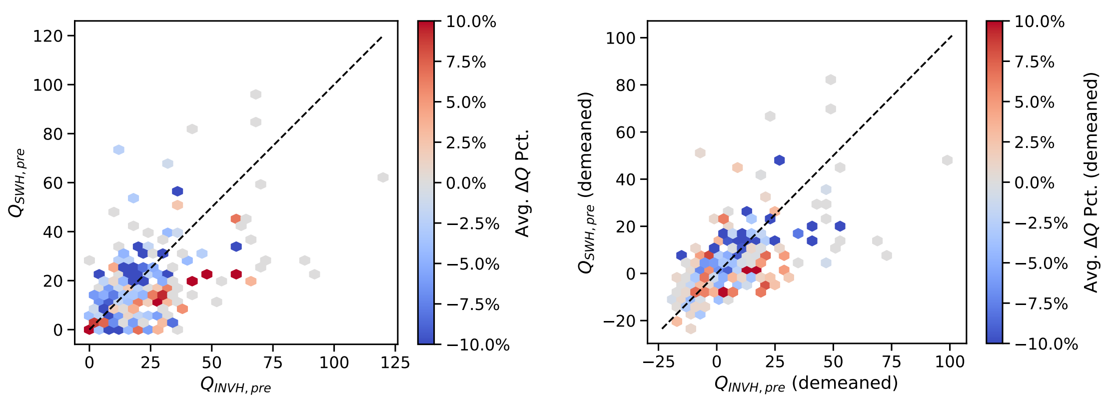
Table B4: Market-level change in number of units and occupancy post merger

	Net Acquisitions Pct	Δ Occupancy	Δ Net Acquisitions Pct
	(1)	(2)	(3)
Intercept	-0.362***	0.017	-0.310**
	(0.109)	(0.017)	(0.099)
Frac Gained in Merger	-0.017	-0.003	-0.022
	(0.021)	(0.003)	(0.019)
NOI Margin	0.540**	-0.018	0.480**
	(0.169)	(0.027)	(0.154)
Observations	12	12	12
R^2	0.534	0.142	0.527

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows regressions of changes in quantities and occupancy on the fraction of INVH's homes in a given market gained in the merger between INVH and SWH in November 2017. The fraction gained in the merger is the SWH quantitiy in a market divided by the INVH quantity in the market in Q4 2017. The NOI margin is the market-level net operating margin. The dependent variable in Column (1) is the market-level organic growth in 2018 divided by the number of homes in the market in Q4 2017. The dependent variable in Column (2) is the 2018 market-level occupancy divided by the 2017 market-level occupancy. The dependent variable in Column (3) is market-level organic growth in 2018 divided by the 2017 market-level organic growth. There are 12 markets in this analysis. Data come from earnings statement supplements for INVH.

Figure B7: Sales of units after merger of Invitation Homes and Starwood Waypoint Homes

Panel A: Pct. of units sold post-merger *Panel B: Pct. of units sold post-merger demeaned by county*



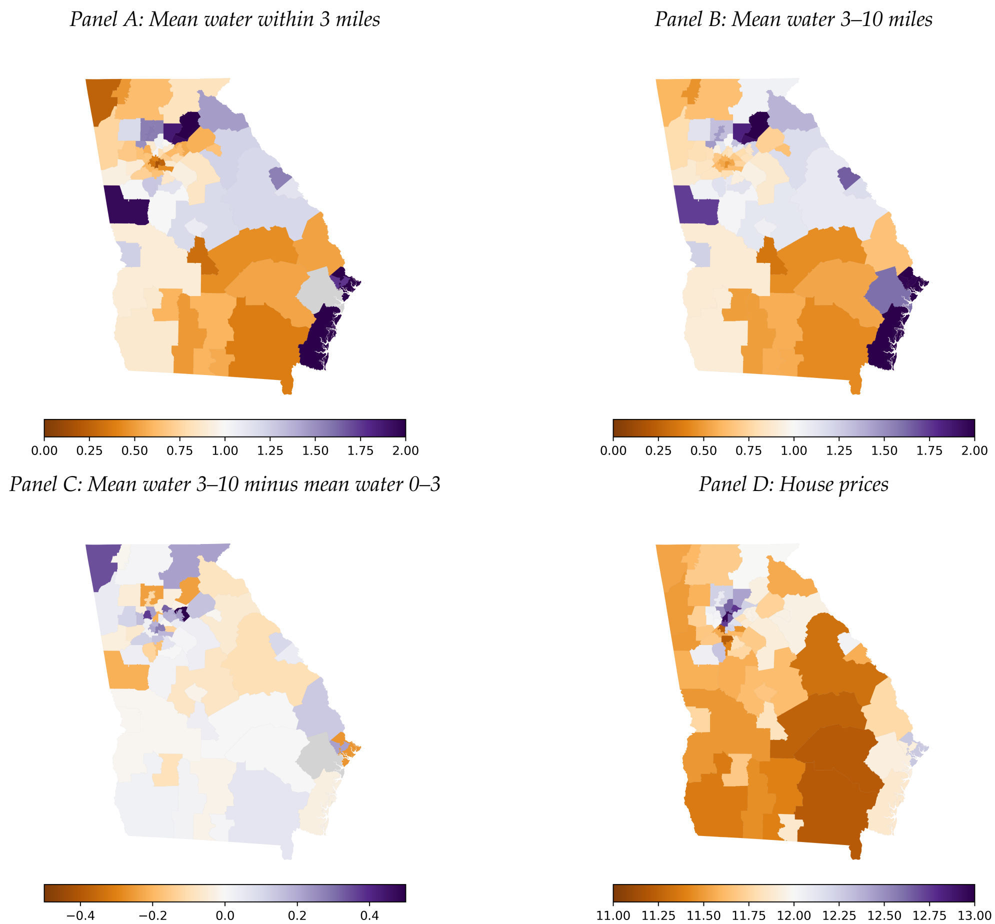
Note: Panel A shows the mean percentage of units sold in a Census Tract by the combined Invitation Homes and Starwood Waypoint Homes entity from November 2017 to November 2018, as a function of the number of units each entity had before the merger at the Census Tract level. The denominator is the number of units owned by the combined entity at the time of the merger, in November of 2017. Panel B shows the same figure after subtracting county level means from the number of units in each tract pre-merger and the percentage change in units post-merger.

Table B5: First stage for household demand

	log(Price)	log(Rent)
log(Land Unavail 0-3mi)	0.0115	-0.0088*
log(Land Unavail 3-10mi)	0.0755***	0.0248***
log(Wetlands 0-3mi)	0.0224	0.0097*
log(Wetlands 3-10mi)	-0.0619***	-0.0002
log(Water 0-3mi)	-0.0629***	-0.0689***
log(Water 3-10mi)	0.0690***	0.0767***
med. year built	0.0004**	0.0003***
med. year built neighboring pumas	0.0002***	0.0002***
med. num rooms	-0.2518***	-0.1022***
med. num rooms neighboring pumas	-0.3098***	-0.1809***
frac. SF census	0.6106***	0.2360***
frac. SF census neighboring pumas	-0.1928***	0.2053***
Weather controls	Y	Y
School controls	Y	Y
Amenity controls	Y	Y
Year FEs	Y	Y
Partial F-stat	909.0	1405.9
n. obs	47395	47395

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the first-stage results of a pooled instrumental variables regression of indirect utilities on characteristics for the whole US from 2012 to 2019. Topography characteristics are described for both the area within 3 miles of the average census tract within a PUMA and the area within a 3–10 mile ring from that census tract. These features are total land unavailability, amount of water, and amount of wetlands, all from Lutz and Sand (2022). Other characteristics shown are the median number of rooms, median year built of housing, and fraction of a PUMA's housing stock that is single-family. These three characteristics are also included for neighboring PUMAs. Instruments are the characteristics for the 3–10 mile rings and the neighboring PUMAs. They are ordered next to the results for the within-3-mile circle for comparison. Partial F statistics for the instruments are reported below.

Figure B8: Examining the instrument



Note: This figure shows some characteristics of topography and prices for Georgia. Panel A shows the mean amount of water within 3 miles of each census tract in a PUMA. Panel B shows the same figure for the 3–10 mile ring around the census tract. Panel C shows the average difference between the mean water 3–10 miles away and the mean water within 3 miles of a given census tract within a PUMA. Panel D shows the mean of the log house price of a PUMA in 2012.

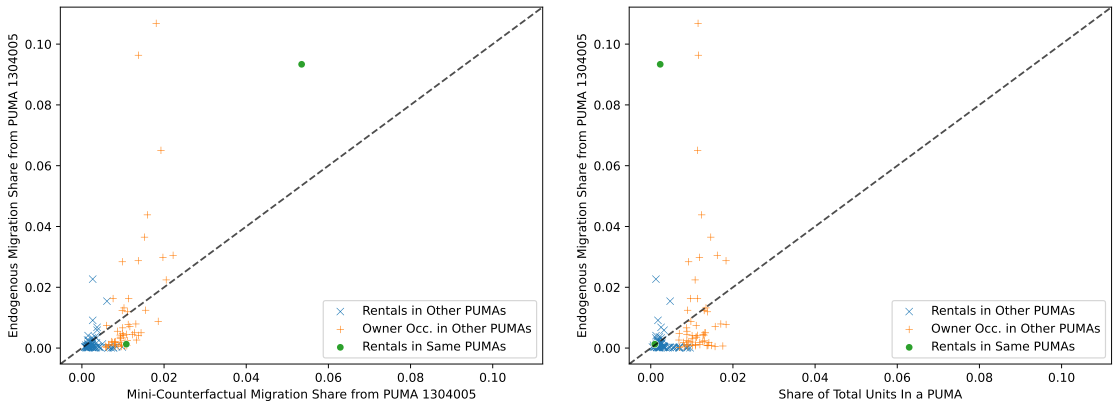
Table B6: Migration share IV

	log(migshare / migshare0)
$sqrt(Distance_{i\to j})$	-0.0003***
$log(SCI_{i\to j})$	0.4280***
$ooc \to ooc$, same puma	-0.7413***
$ooc \to ooc$, diff puma	-7.7582***
$ooc \to sf$, same puma	-4.8933***
$ooc \to mf$, same puma	-8.0104***
$ooc \to sf$, diff puma	-8.2170***
$ooc \to mf$, diff puma	-8.8467***
$sf \to ooc$, same puma	-2.5095***
$sf \to ooc$, diff puma	-6.3025***
$sf \to sf$, same puma	-1.1699***
$sf \to mf$, same puma	-6.7959***
$sf \to sf$, diff puma	-6.6098***
$sf \to mf$, diff puma	-7.2638***
$mf \to ooc$, same puma	-2.4032***
$mf \to ooc$, diff puma	-4.3695***
$mf \to sf$, same puma	-3.3534***
$mf \to mf$, same puma	-0.0115
$mf \to sf$, diff puma	-4.6659***
$mf \to mf$, diff puma	-5.3508***
$log(Rent)$	-0.2640***
$log(Price)$	-0.1277***
Topography controls	Y
Weather controls	Y
Housing characteristics controls	Y
Amenity controls	Y
n. obs.	3303095

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the IV regression of the log share of a PUMA's residents who move from origin i to destination j divided by the share moving to the outside asset. The outside asset is defined as all PUMAs missing data on a nonprice characteristic, with housing prices below \$80k or with rent below \$500. This is a pooled regression using bilateral migration data from 2012 to 2019 from Verisk.

Figure B9: Comparison of Substitution Patterns with Endogenous Migration Shares

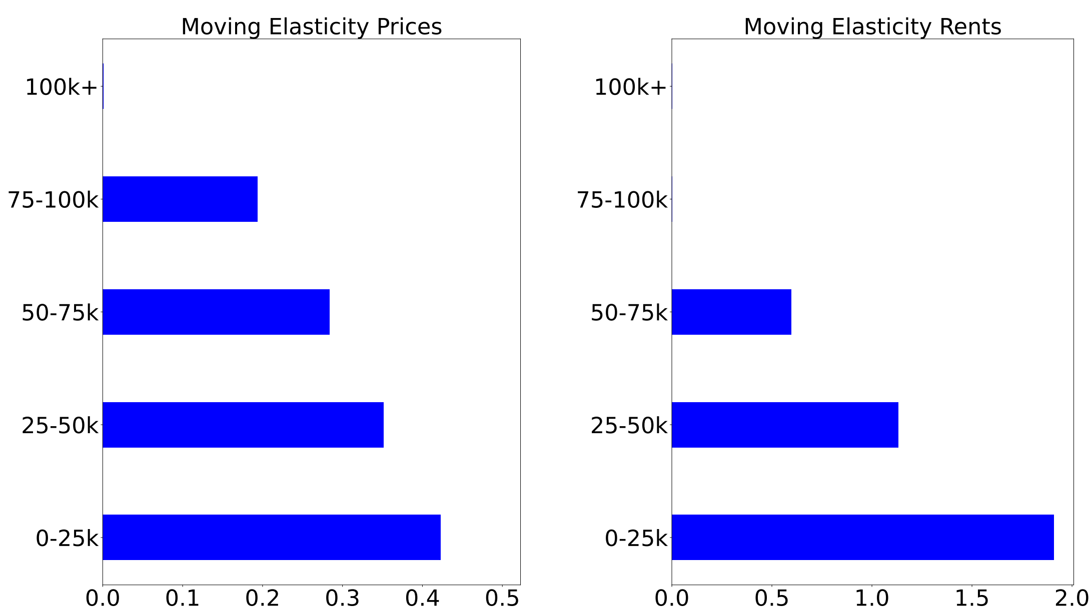
Panel A: Model substitution patterns *Panel B: Houshold holdings share*



Notes: This figure shows the PUMA-level migration patterns from a simulation where the price of owner-occupied housing in one PUMA in the Atlanta suburbs, PUMA 1304005, is increased by 10%. Panel A shows the migration shares from a counterfactual where I raise the price of owner-occupied housing in one PUMA in the Atlanta suburbs. It compares these shares to observed endogenous migration shares. Panel B shows the household housing holdings shares and compares this to the observed endogenous migration shares.

Figure B10: Demand elasticities

Panel A: Owners *Panel B: Renters*



Notes: This figure shows the PUMA-level moving elasticities with respect to prices and rents of aggregate groups of households as estimated by the demand system. I estimate the elasticities using American Community Survey 1-year (ACS1) data from 2012 to 2019 at the PUMA× year level. The elasticity is the percentage by which each group's quantity decreases when price or rent increases by 1%.

Table B7: Household estimation for rental housing

Parameter	0-25k	25-50k	50-75k	75-100k	100k+
Log(Rent)	-1.909***	-1.132***	-0.597***	-0.001	-0.001
	[-2.17, -1.64]	[-1.39, -0.88]	[-0.85, -0.34]		
Med. Year Built	0.000	0.001***	0.001***	0.001**	0.001***
	[-0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]
Med. Number of Rooms	-0.098***	-0.068***	-0.118***	-0.187***	-0.527***
	[-0.15, -0.04]	[-0.12, -0.02]	[-0.17, -0.06]	[-0.23, -0.14]	[-0.57, -0.48]
Frac. Single Family Rentals	-0.777***	-0.552***	-0.397***	-0.372***	-0.109
	[-0.92, -0.63]	[-0.69, -0.41]	[-0.56, -0.23]	[-0.55, -0.19]	[-0.28, 0.06]
Frac. Less 45 Min Commute	0.112	0.712***	1.063***	1.178***	0.358***
	[-0.12, 0.35]	[0.49, 0.94]	[0.81, 1.31]	[0.96, 1.4]	[0.14, 0.57]
Frac. High School Enrollment	-0.351*	-0.035	0.284	0.783***	2.244***
	[-0.73, 0.03]	[-0.41, 0.33]	[-0.1, 0.67]	[0.35, 1.22]	[1.76, 2.73]
Frac. High School Private	0.026	-0.376***	-0.256*	0.138	1.227***
	[-0.22, 0.27]	[-0.62, -0.13]	[-0.52, 0.0]	[-0.08, 0.36]	[1.02, 1.43]
Log(Distance All)	-0.125***	-0.059***	-0.037***	-0.053***	-0.047***
	[-0.14, -0.11]	[-0.07, -0.04]	[-0.05, -0.02]	[-0.08, -0.03]	[-0.07, -0.02]
Log(Distance Top 30)	-0.029**	-0.048***	-0.078***	-0.104***	-0.178***
	[-0.05, -0.01]	[-0.07, -0.03]	[-0.1, -0.06]	[-0.12, -0.09]	[-0.2, -0.16]
log(Distance to Coast)	-0.041***	-0.006	0.005	-0.013*	-0.074***
	[-0.06, -0.02]	[-0.02, 0.01]	[-0.01, 0.02]	[-0.03, 0.0]	[-0.09, -0.06]
Jan. Temp.	0.016***	0.013***	0.013***	0.012***	0.013***
	[0.01, 0.02]	[0.01, 0.01]	[0.01, 0.01]	[0.01, 0.01]	[0.01, 0.02]
Jan. Sunlight	0.003***	0.002***	0.002***	0.001***	0.002***
	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]
July Temp.	-0.028***	-0.020***	-0.018***	-0.018***	-0.016***
	[-0.03, -0.02]	[-0.02, -0.02]	[-0.02, -0.01]	[-0.02, -0.01]	[-0.02, -0.01]
July Humidity	-0.002***	-0.001***	-0.002**	-0.002***	-0.004***
	[-0.0, -0.0]	[-0.0, -0.0]	[-0.0, -0.0]	[-0.0, -0.0]	[-0.01, -0.0]
log(Land Unavail 3mi)	-0.033***	-0.066***	-0.062***	-0.074***	-0.033***
	[-0.05, -0.02]	[-0.08, -0.05]	[-0.07, -0.05]	[-0.09, -0.05]	[-0.06, -0.01]
log(Wetlands 3mi)	-0.037***	-0.010*	-0.008	-0.006	-0.002
	[-0.05, -0.02]	[-0.02, 0.0]	[-0.02, 0.0]	[-0.02, 0.01]	[-0.02, 0.02]
log(Water 3mi)	0.037***	0.040***	0.034***	0.030***	0.025**
	[0.02, 0.05]	[0.03, 0.05]	[0.02, 0.05]	[0.01, 0.05]	[0.0, 0.05]
Single Family Rental	-1.047***	-0.939***	-0.838***	-0.665***	-0.248***
	[-1.13, -0.97]	[-1.02, -0.86]	[-0.92, -0.76]	[-0.69, -0.64]	[-0.28, -0.22]
Log(Rent) (OLS)	-1.478***	-0.630***	-0.001	-0.001	-0.001
	[-1.54, -1.41]	[-0.69, -0.57]			
Log(Rent) (Leave-out IV)	-1.441***	-0.684***	-0.158	-0.001	-0.001
	[-1.70, -1.18]	[-0.94, -0.43]	[-0.42, 0.10]		

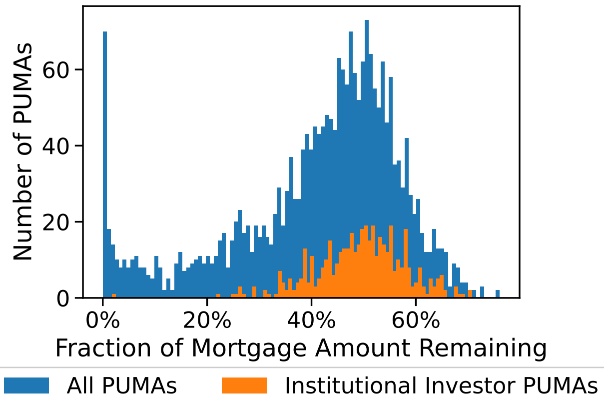
Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the estimation results for Equation (25) at the PUMA and rental housing type level. Coefficients shown are for log(Rent), median year built and median number of rooms of rental housing, fraction of the PUMA that is SF housing, fraction of households commuting fewer than 45 minutes, fraction of high school aged population enrolled in high school, fraction of the same group enrolled in private school, log(distance to nearest MSA), log(distance to nearest top 30 MSA), weather, topography, and an indicator for whether the row is for SF or MF. Year fixed effects are included. Rents are different for SFR and MFR. Elasticity with respect to rent is constrained to be -0.001 for highest income groups. Coefficients for log(Rent) for OLS and leave-out specifications (exclude PUMAs where institutional investors own 200+ units) are shown for comparison.

Table B8: Household estimation for owner-occupied housing

Parameter	0-25k	25-50k	50-75k	75-100k	100k+
Log(Price)	-0.423***	-0.352***	-0.284***	-0.194***	-0.001
	[-0.48, -0.36]	[-0.4, -0.3]	[-0.33, -0.23]	[-0.25, -0.14]	
Med. Year Built	-0.000	0.000**	0.000***	0.001*	0.000***
	[-0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[-0.0, 0.0]	[0.0, 0.0]
Med. Number of Rooms	-0.028**	-0.028**	-0.041***	-0.054***	-0.157***
	[-0.06, -0.0]	[-0.05, -0.0]	[-0.06, -0.02]	[-0.08, -0.03]	[-0.17, -0.14]
Frac. Single Family Rentals	0.077**	0.310***	0.405***	0.490***	0.698***
	[0.01, 0.14]	[0.24, 0.38]	[0.35, 0.46]	[0.43, 0.55]	[0.64, 0.75]
Frac. Less 45 Min Commute	-0.249***	-0.114**	-0.140***	-0.174***	-0.259***
	[-0.37, -0.12]	[-0.22, -0.01]	[-0.24, -0.04]	[-0.29, -0.06]	[-0.33, -0.19]
Frac. High School Enrollment	-0.347***	-0.190**	-0.040	0.124	0.645***
	[-0.52, -0.17]	[-0.35, -0.02]	[-0.19, 0.11]	[-0.03, 0.28]	[0.51, 0.78]
Frac. High School Private	0.408***	0.285***	0.287***	0.291***	0.670***
	[0.29, 0.52]	[0.19, 0.38]	[0.19, 0.38]	[0.2, 0.39]	[0.6, 0.74]
Log(Distance All)	0.013**	0.017***	0.016***	0.019***	0.029***
	[0.0, 0.02]	[0.01, 0.03]	[0.01, 0.02]	[0.01, 0.03]	[0.02, 0.04]
Log(Distance Top 30)	0.013***	-0.012***	-0.030***	-0.040***	-0.069***
	[0.01, 0.02]	[-0.02, -0.01]	[-0.04, -0.02]	[-0.05, -0.03]	[-0.07, -0.06]
log(Distance to Coast)	-0.007*	-0.001	0.001	0.002	-0.002
	[-0.01, 0.0]	[-0.01, 0.0]	[-0.0, 0.01]	[-0.0, 0.01]	[-0.01, 0.0]
Jan. Temp.	0.003***	0.000	-0.001	-0.002***	-0.002***
	[0.0, 0.0]	[-0.0, 0.0]	[-0.0, 0.0]	[-0.0, -0.0]	[-0.0, -0.0]
Jan. Sunlight	0.002***	0.001***	0.001***	0.001***	0.001***
	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]
July Temp.	-0.006***	-0.004***	-0.003***	-0.002*	0.004***
	[-0.01, -0.0]	[-0.01, -0.0]	[-0.01, -0.0]	[-0.0, 0.0]	[0.0, 0.01]
July Humidity	0.001***	0.001***	0.001***	0.001***	0.002***
	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]
log(Land Unavail 3mi)	0.062***	0.030***	0.013***	0.004	0.003
	[0.05, 0.07]	[0.02, 0.04]	[0.01, 0.02]	[-0.0, 0.01]	[-0.0, 0.01]
log(Wetlands 3mi)	-0.021***	-0.010***	-0.004	-0.000	0.002
	[-0.03, -0.01]	[-0.02, -0.0]	[-0.01, 0.0]	[-0.01, 0.01]	[-0.0, 0.01]
log(Water 3mi)	0.010**	0.011**	0.009**	0.007*	0.002
	[0.0, 0.02]	[0.0, 0.02]	[0.0, 0.02]	[-0.0, 0.01]	[-0.01, 0.01]
Log(Price) (OLS)	-0.404***	-0.306***	-0.172***	-0.049***	-0.001
	[-0.42, -0.39]	[-0.32, -0.29]	[-0.19, -0.16]	[-0.06, -0.04]	
Log(Price) (Leave-out IV)	-0.500***	-0.373***	-0.287***	-0.186***	-0.001
	[-0.57, -0.43]	[-0.43, -0.31]	[-0.34, -0.23]	[-0.25, -0.13]	

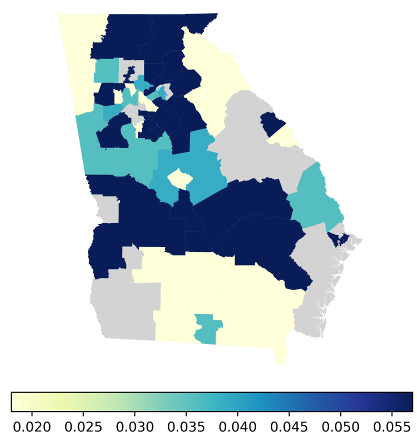
Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the estimation results for Equation (25) at the PUMA level for owner-occupied housing. Coefficients shown are for log(House Price), median year built and median number of rooms of owner-occupied housing, fraction of the PUMA that is SF housing, fraction of households commuting fewer than 45 minutes, fraction of high school aged population enrolled in high school, fraction of the same group enrolled in private school, log(distance to nearest MSA), log(distance to nearest top 30 MSA), weather, and topography. Elasticity with respect to price is constrained to be -0.001 for highest income group. Year fixed effects are included. Elasticity with respect to price is constrained to be -0.001 for highest income group. Coefficients for log(House Price) for OLS and leave-out specifications (exclude PUMAs where institutional investors own 200+ units) are shown for comparison.

Figure B11: PUMA-level average fraction of mortgage amount remaining for small landlords



Note: This figure shows the histogram at the census PUMA level of the average small landlord mortgage balance outstanding as a fraction of the sale price. The blue histogram shows the figures for all PUMAs, and the orange shows the figures for PUMAs where the 7 institutional investors studied in this paper owned at least 100 units combined as of November 2019. The small landlord mortgage balance outstanding is constructed from data on mortgage origination balances and an assumption of 30-year mortgage terms and linear amortization. When mortgage balances are present but sales prices are missing, sales prices are imputed with the sale year and PUMA-level average. The dataset for mortgage balances is from November 2015; only properties with sales in 2012 or earlier are used here.

Figure B12: Expected rent growth



Note: This figure shows the expected rent growth from 2012 onward for both types of landlords. Expected rent growth comes from a regression of 2006–2012 rent growth on an indicator for above-median national population growth, above-median national job growth, and state fixed effects. The resulting distribution's mean is set to the expected national 5-year rent growth from 2014 from the New York Federal Reserve Bank's Survey of Consumer Expectation (SCE) data. The year 2014 is the earliest for which the SCE data are publicly available.

Table B9: Small landlord estimation

	Georgia	High Investor Activity
Corr($Q_{est,PUMA}$,$Q_{actual,PUMA}$)	94%	96%
Median $Q_{est,PUMA}$ / $Q_{actual,PUMA}$	1.04	1.12
Median Elasticity with Respect to Rent	0.55	0.34
Median Elasticity with Respect to Price	-0.53	-0.33

Note: This table shows estimation results with actual 2012 rents and prices for the small landlord estimation. I compare the estimated PUMA quantities to the actual quantities in 2012 for all of Georgia and for PUMAs where institutional investors have 1000 or more units, which I call high-investor-activity regions. I first report the correlations between the estimated quantities and the actual quantities. Then, I report the median of the estimated quantity divided by the actual quantity. Next, I raise rents by 1%, measure the change in quantity in each region and report the median change as the median elasticity with respect to rent. Finally, I raise prices by 1%, measure the change in quantity in each region and report the median as the median elasticity with respect to price.

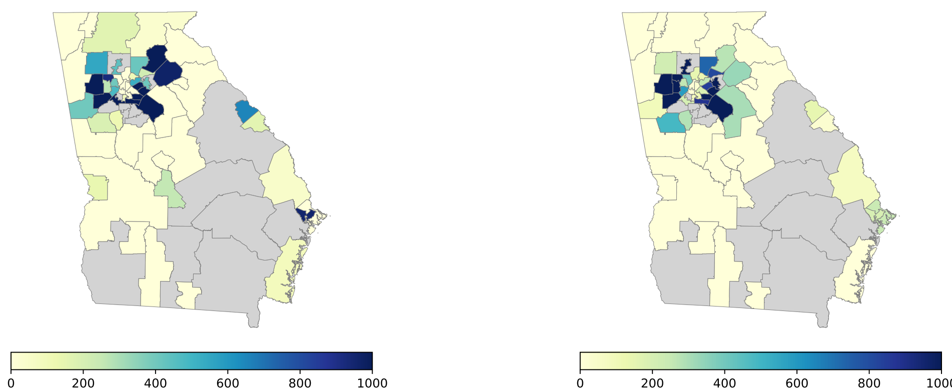
Table B10: Small landlord fitted elasticities

	Dependent variable: Elasticity with respect to price
	Georgia
	(1)
Intercept	22.33***
	(3.65)
Expected Rent Growth Pct	0.36***
	(0.11)
Log(Price/Rent)	-4.31***
	(0.65)
Mean Mortgage Balance Pct	-2.37*
	(1.23)
Property Tax Rate Pct	-0.41
	(0.68)
Observations	57
R^2	0.55

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the regression of fitted small landlord elasticities on components of their objective function in Georgia. The dependent variable is the percentage change in small landlord quantity when prices increase by 1%. "Expected Rent Growth Pct" is g_j, "log(Price/Rent)" is the PUMA-level price-to-rent ratio in 2012, "Mean Mortgage Balance Outstanding Pct" is the PUMA-level small landlord average mortgage balance outstanding, and "Property Tax Rate Pct" is the property tax in percent terms.

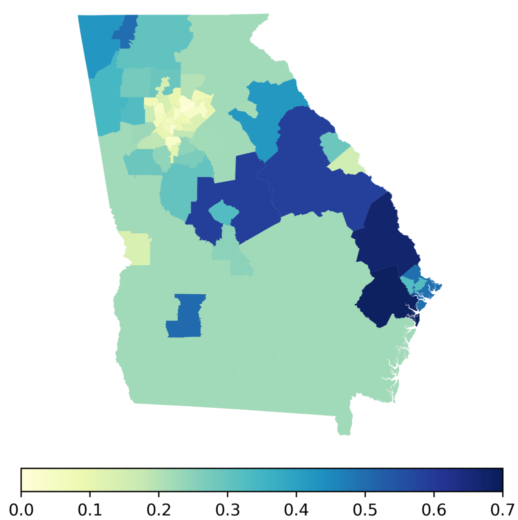
Figure B13: Large landlord estimation fit

Panel A: Estimated large landlord quantities *Panel B: Actual quantities*



Note: I estimate the quantities chosen by 3 identical large landlords and plot the sum for Georgia in Panel A. I compare these estimates to the actual institutional investor quantities in 2019 in Georgia in Panel B.

Figure B14: Supply elasticities for Georgia



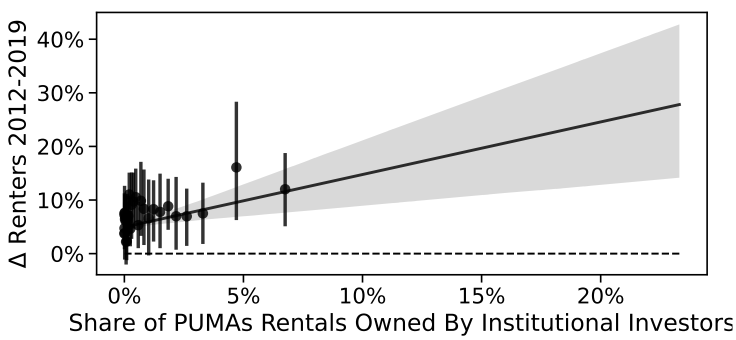
Note: This figure shows the new unit supply elasticities for Georgia, aggregated from the census tract–level elasticities from Baum-Snow and Han (2024). Missing PUMA elasticities are imputed with the state-level mean, which here is 0.22.

Table B11: Association of landlord exits with institutional investor entry

	Dependent variable: $\Delta Q_{other,cty,tr}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Q_{inst,cty,tr}$	-0.599***	-0.563***	-0.535***	-0.691***	-0.643***	-0.634***
	(0.075)	(0.076)	(0.084)	(0.080)	(0.081)	(0.085)
FE Level	None	State	County	None	State	County
Intensive Margin	N	N	N	Y	Y	Y
Observations	13620	13620	13620	8320	8320	8320

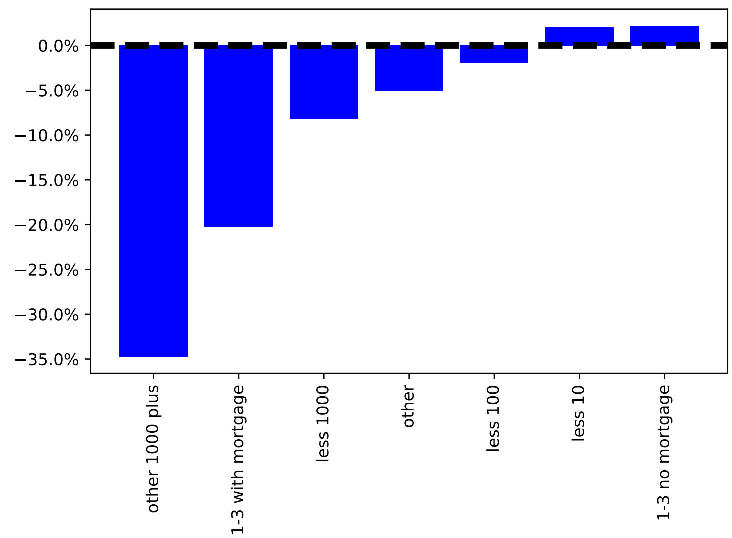
Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the results from regressions of the change in non-institutional landlord holdings at the census tract level on the change in institutional landlord holdings from 2016–2021. Columns (1)-(3) are on the extensive margin and have no fixed effects, state fixed effects, and then county fixed effects. Columns (4)-(6) include only tracts where institutional investors gained homes during this time period and include the same series of fixed effects.

Figure B15: Change In Renters Observational Data



Note: This chart shows a binscatter of the change in the number of renters in each PUMA by the fraction of the total PUMAs rental stock owned by one of the 7 institutional investors in this paper in 2019. Data comes from the Census ACS1 PUMS. The chart is for the whole US. The dotted black line shows a 0% increase in renters in a PUMA.

Figure B16: Association of landlord exits by landlord type



Note: This chart shows the coefficients from regressions of the change in a specific landlord type's holdings at the census tract level on the change in institutional landlord holdings from 2016–2021 with county fixed effects. The regression is run for landlords with more than 1000 homes who are not classified as institutional investors who buy homes to rent, landlords with 1-3 homes who have mortgage data, landlords with 101-999 homes (less 1000), other types of landlords including flippers and investment companies, landlords with 11-99 homes (less 100), landlords with 4-9 homes (less 10), and landlords with 1-3 homes who have no mortgage data. Data on landlords comes from Verisk.