The Impact of Institutional Investors on Homeownership and Neighborhood Access*

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Abstract

Since 2012, institutional investor entry into the single-family rental market in the suburbs of US cities has coincided with higher price and rent growth in those areas than in the rest of the country. To determine the consequences of institutional investors' impact on the housing market, this paper estimates a structural model where institutional investor landlords benefit from economies of scale and market power. While the institutional investor demand shock decreased homeownership and raised prices locally, supply responses dampened these effects, resulting in a homeownership decrease of 0.23 homes for each home purchased and a price increase of at most 27% of the observed price increase in markets where institutional investors entered. Institutional investors decreased rents on net despite the presence of market power because they increased the supply of rentals. Overall, institutional investor entry resulted in a tradeoff: Renters benefited from lower rents and more rentals in locations with better schools, but prospective homeowners had a harder time buying homes because of higher prices.

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I Introduction

Historically, large landlords have focused on multifamily housing. However, since 2012, institutional investors have entered the single-family rental market and purchased up to 8.5% of the housing stock in some zip codes in the suburbs of 10–20 US cities, including Atlanta, Phoenix, and Tampa. The new institutional investor landlords differ from existing "mom-and-pop" landlords: They have portfolios of up to 85,000 rather than 1–3 homes, and their assets are spatially concentrated. 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 and 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 investments in single-family homes[1] and a 5% rent increase cap for corporate landlords.[2] However, the construction sector can respond to a demand shock by building homes, and small landlords may do so by selling their homes—both responses that might offset some of the impact on homeownership and prices. In addition, the net effect of institutional investor entry on rents depends on whether market power leads the new entrants to decrease rental supply or, instead, low operating costs lead them to increase rental supply. The implications of institutional investor entry for the housing market depend on large landlords' underlying incentives and the margins of adjustment along which others in the housing market respond.

This paper examines how institutional investor landlords differ from "mom-and-pop" landlords and the implications of the entry of the former for the housing market. By estimating a structural model of the housing market with landlords that are heterogeneous in operating costs and market power, I find that institutional investors raised 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 0.23 homes for each home purchased. Despite the presence of market power, I show that large landlords increased rental supply by 0.56 homes for each home purchased and decreased rents on net. The renters who moved into the institutional investor rentals came from regions with worse

[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%."

schools and historical economic mobility. I conclude that policies seeking to ban institutional investors or cap 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 locations with good schools but made it harder for prospective homeowners to buy homes.

I begin by describing the activity of 7 large institutional investors that, from 2012, bought homes to supply as rentals. Institutional investors targeted suburbs of cities with low price-to-rent ratios that experienced many foreclosures during the great recession. While these 7 companies owned only 0.17% of the total US housing supply as of February 2021, they had purchased 5.7% of the housing stock in Paulding County, Georgia, for example, and up to 19% of the housing stock in some census tracts in only 9 years. The institutional investors purchased homes in areas with few rentals, which led to the 7 companies having a combined rental market share of up to 78% in some census tracts. Individual-level data show that the renters who moved into institutional investor homes came from areas with lower median household incomes, middle-school math test scores, and historical economic mobility. Institutional investor presence is associated with increases in house prices and rents relative to those in the rest of the US. Large landlords' entry in the single-family rental market, their concentrated buying, and the association of their entry with price and rent increases account for the considerable public interest in these investors.

Institutional investor landlords operate at lower average costs and scale more efficiently than existing "mom-and-pop" landlords. Two public single-family rental real estate investment trusts (REITs), Invitation Homes (INVH) and American Homes for Rent (AMH), pay lower property taxes, operating expenses, and insurance expenses as a fraction of rent than small landlords. This is because these large landlords' scale allows them to efficiently appeal property tax values, as documented in Austin (2022), and bargain with insurers and contractors for bulk discounts. The slopes of their cost curves are different from those of small landlords, as well. The latter minimize cash expenses in ways that do not scale: Most do not hire managers or have mortgages. Because debt and managers are necessary for scaling, small landlords must increase their cash costs to scale and therefore have decreasing returns to scale. Institutional investors, on the other hand, have vertically integrated management teams, high debt, and a lower debt cost. INVH's portfolio size increased by 64% in a merger, and its operating expenses per home did not increase, suggesting that it has constant returns to scale in the portion of the variation that we are able to observe. Lower average costs and constant returns to scale lead institutional investors to accumulate large portfolios where they operate. Large portfolios can give rise to market power by fostering an incentive to internalize the impact of quantity choice on rent.

I explore the implications of housing providers' cost curve differences by modeling institutional investor behavior in a structural model that includes households, small landlords, and construction. Key features of the model are that small landlords have decreasing and large landlords constant returns to scale. The latter can accumulate portfolios large enough to internalize the impact of their quantity choice on rents and therefore behave as Cournot oligopolists.

To answer quantitative questions such as whether institutional investor entry decreases homeownership and how many renters would not live in the respective neighborhoods if institutional investors had never entered the market, the model incorporates rich substitution patterns for households. Households choose where to live and whether to own their housing, rent single-family housing, or rent a unit in multifamily housing by solving a discrete-choice problem. I estimate household demand with data from the Census American Community Survey (ACS), similarly to Bayer, Ferreira and McMillan (2007), Calder-Wang (2022), and Diamond (2016). I calibrate geographic substitution patterns with bilateral migration data from Verisk (formerly Infutor). I estimate demand for different household groups based on their income, which leads to different price and rent elasticities, allowing institutional investor entry to have heterogeneous impacts and households to have heterogeneous responses. Elasticities for prices and rents are identified with an instrumental variable (IV) strategy.

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

Rental supply in the model is determined endogenously by the sum of the demand from large and from small landlords. This setup allows for the possibility that large landlords crowd out small landlords. To estimate small landlords' demand, I aggregate individual small landlords' decisions to operate rentals or sell their properties. Large landlords 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 equilibrium rents and prices.

I estimate the impact of 3 identical institutional investors entering the housing market in 2012 and choosing 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.

I find that the institutional investors' entry decreased the number of homes available for owner occupancy by 0.23 for each home they purchased. The demand shock triggered a construction response and crowded out small landlords: Builders built 0.33 homes, and small landlords sold 0.44 homes. A back-of-the-envelope calculation that failed to consider the supply responses would overestimate the investors' impact on homeowership by a factor of 4. The institutional investors' entry increased the number of rentals by 0.56 for each home they purchased. The model shows that low-income renters moved into the rentals supplied by the institutional investors—a finding that aligns with the data showing that renters from lower-income areas moved into the investors' rental homes—and therefore that the institutional investors' entry increased neighborhood access for low-income renters.

Further, the estimation implies that in the regions where the institutional investors bought the most housing, they caused 27% of the observed increase in local housing prices. In the regions where the institutional investors bought a smaller share of the housing stock, almost all of the observed local price increase would have occurred even without the institutional investor demand shock. The institutional investors decreased rents by 0.7 pp for every 1 pp of the rental stock that they own because, on net, they increased the supply of single-family rentals. In other words, the sign of the effect of their entry is opposite that of the observed association between institutional investor presence and rent increases. The difference in size between the model-implied and the observed price increases, and the difference in sign between the model-implied and the observed changes in rent, are consistent with the investors having incentives to target regions with expected rent and price growth. I document that the areas where the institutional investors purchased homes experienced large increases in population relative to that in the rest of the country after the investors' entry.

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 compare the rent impacts to those in Gurun, Wu, Xiao and Xiao (2023), which uses quasi-experimental evidence from mergers to examine the effect of concentration on rents. I find that such a merger would increase rents in areas of overlap between the merging housing providers by a median of 0.71%, a magnitude consistent with that of the rent increase in Gurun et al. (2023).

I then simulate two proposed policies. One is a tax of $10k per home per year levied on operators with more than 50 single-family units. This tax would more than double operating expenses, effectively banning institutional investors from operating single-family rentals. I simulate this policy by removing institutional investors from the market in 2019 and find that prices would decrease, rents would increase, and small landlords would gain a large share of the homes that institutional investors would be forced to sell. I also simulate a 5% cap on rent increases for large landlords. I find that this cap would lower the quantity of rentals that large landlords supply. The results show that policies not accounting for the fact that institutional investors increase the quantity of rentals can have the opposite of their intended effects on rents.

This paper is the first to develop a structural model designed to estimate the total market-level impacts of institutional investor entry on the housing market. Several papers describe institutional investor activity in single-family housing markets and its associations with housing market trends, including Mills, Molloy and Zarutskie (2019), Gould Ellen and Goodman (2023), Demers and Eisfeldt (2022), and Giacoletti, Heimer, Li and Yu (2024). Ganduri, Xiao and Xiao (2022) and Lambie-Hanson, Li and Slonkosky (2022) study the role of these investors in increasing prices following the financial crisis. Garriga, Gete and Tsouderou (2023) estimate price impacts of small and medium investors on the purchase and rental markets. Gurun et al. (2023) and Austin (2022) study the effect of increasing concentration on rents, prices, and crime. Billings and Soliman (2023) study the effect of institutional investor entry on neighboring housing prices. An (2023) studies the associations of institutional investor presence with decreased Black homeownership rates. Gorback, Qian and Zhu (2024) study the effect of these investors' activity on prices and rents. Francke, Hans, Korevaar and van Bekkum (2023) study the effect of a ban on investor purchases in the Netherlands on neighborhood housing prices and demographics.

My research differs from the work above in five main ways. First, I can compare the size of the market power effect with that of the gains in operational efficiency of the large landlords and find that the market power effect on rents is relatively small and therefore that institutional investor entry caused a net decrease in rents. If policymakers considered only the market power channel, they would misperceive not only the size of the impact on rents but also its direction. Therefore, policies aimed at lowering rents by banning investors are counterproductive, as I show in a policy simulation. Second, I use the structural model to quantify the total impact of institutional investors' market presence on homeownership. The model accounts for the fact that people can move to become homeowners elsewhere and then supply can respond in the destination locations. The literature has not been able to quantify the total impact of institutional investor entry on homeowership. A back-of-the-envelope calculation of this homeowership impact that does not consider supply responses would overestimate the impact by a factor of 4. Third, I perform counterfactual analysis to isolate the economic channels of the identified effects and simulate policy proposals. I simulate a ban on institutional investors as rental housing providers and a 5% cap on rent increases and show, similarly to other researchers investigating the effects of rent control such as Diamond, McQuade and Qian (2019), that both policies would reduce rental supply and increase rents. Fourth, underlying all of these results is a novel analysis of operating costs by landlord type that demonstrates how the operating costs of financial intermediaries in real estate impact the housing market. Finally, I use individual-level location data to show that renters who move into institutional investor rentals tend to come from lower-income areas with worse schools.

There are several mechanisms through which institutional investors could affect households that I do not study: For example, Raymond, Duckworth, Miller, Lucas and Pokharel (2018) find that corporate landlords in their setting are more likely to evict than other landlords. Additionally, the Federal Trade Commission (FTC) recently fined Invitation Homes for its use of deceptive fees.[3] Moreover, it is possible that institutional investors renovate homes to improve their quality. While these are important mechanisms that could affect households, they are also operative in multifamily housing markets and across landlord types. This paper focuses on mechanisms specific to the entry of large landlords into the single-family rental market.

I also contribute to the literature on market power in housing. Calder-Wang and Kim (2024) study how algorithmic pricing can lead to market power in the multifamily rental segment. Watson and Ziv (2024) study market power in the multifamily rental market in New York City. My paper focuses on market power in the single-family rental market, which is more liquid than the multifamily rental market and therefore features a trade-off between rents and quantity rather than rents and vacancies. While market power

[3] https://www.ftc.gov/news-events/news/press-releases/2024/09/ftc-takes-action-against-invitation-homes-deceiving-renters-charging-junk-fees-withholding-security

decreases the quantity of rentals in a region and raises rents, in my setting, the available rentals then go to either homeowners or other landlords rather than become vacant. Gurun et al. (2023) study a merger between landlords of single-family units to measure market power. My paper differs from theirs in that I can compare the effect of market power on rents to the effect of institutional investors' increased cost efficiency on rents to estimate the net effect. I find that the cost efficiency channel dominates the market power channel, leading to a net rent decrease.

I also contribute to the literature on models of asset demand. Koijen and Yogo (2019), Koijen, Richmond and Yogo (2023), and Jiang, Richmond and Zhang (2023) use demand systems to examine stock market flows and international asset flows. McFadden (1978), Bayer, McMillan and Rueben (2003), Bayer et al. (2007), Diamond (2016), Calder-Wang (2022), and Almagro and Dominguez-Iino (2024) use discrete-choice models to study housing demand. I use bilateral migration data to estimate heterogeneous moving costs in utility terms for households from different origin locations to each destination region. I use the estimated moving costs in the discrete-choice model to obtain realistic spatial substitution patterns in a static model.

II Data

II.A 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 cut of the data. The dataset contains cross sections for February 2021 and each year from November 2015 to 2019. Each row contains information on property characteristics, mortgage amounts, and anonymized owner mailing addresses. I exclude nonresidential and vacant properties from the analysis. I also exclude properties with no street information, mobile homes, and remaining properties with a duplicate address indicator. These restrictions reduce the dataset for analysis to 110 million residential units. Full details on the construction of this dataset are in Appendix A. I compare these to zip code–level housing unit counts in the Census ACS 5-year tables for 2020 in Appendix Table A1. The R^2 with respect to the census number of housing units is 94% for all units, 96% for owner-occupied units, and 74% for rental units. The dataset undercounts rental units by approximately 8% because of issues with how units for multifamily properties are counted in the data.

I identify institutional investors in the single-family homes market by the mailing addresses to which property tax forms are sent. Following Ganduri et al. (2022), I look at mailing addresses with zip codes among those with the most single-family properties in the US and then use Google to identify the companies that own properties. In this paper, I focus on 7 companies that own the most single-family homes and then rent them out: 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 am able to 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 validate the number of homes I find for them in the data with the numbers listed in their Securities and Exchange Commission (SEC) filings. For February 2021, I can identify 86–91% of these companies' properties, as shown in Appendix Table A2. Tricon Residential is no longer a public company and was purchased by Blackstone in 2024.

For the descriptive analysis, I aggregate the property-level information to the owner–PUMA (census public-use microdata area) level. PUMAs are census geographies with approximately 100,000–200,000 people. I choose the PUMA as the level of aggregation because it is 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 me to use tables created from 5-year averages, which would make it difficult for me 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. For the parts of the descriptive analysis where I do not merge the property-level data with the census data, I aggregate the property data to the zip code–owner and census tract–owner levels. I observe the number of foreclosures from 2007 to 2011 at different geographic levels from Zillow ZTRAX. I also use US geography shapefiles to construct the variable for distance to the nearest city. I merge data at the census tract level to middle-school math test scores from 2013 from Opportunity Insights.

Housing completions at the PUMA level come from the Verisk dataset's property count by year built. The resulting sample aligns with the completions in the Federal Reserve Economic Data up to 2018, as shown in Appendix Figure A1. To infer the amount of new construction at the PUMA level between 2012 and 2019, I extrapolate the annual completion rates for each PUMA from 2012 to 2018.

The property records contain mortgage data including the mortgage origination amount, origination date, and term length for up to the 3 most recent mortgages on a property, including refinancings. I use these mortgage data to study the financing for existing single-family rentals for small landlords. For approximately 10% of the single-family rentals with mortgages, I observe mortgage rate information. From these data, I assemble an empirical distribution of mortgage amounts for each PUMA. To obtain a mortgage balance outstanding distribution for each PUMA, I start with the mortgage origination distribution and assume linear amortization for a 30-year mortgage term.

II.B Rental Housing Finance Survey

Small landlord operating costs and additional financing information come from the Rental Housing Finance Survey (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. The dataset does not provide information on how many properties an owner owns, and it 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 RHS, 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 landlords,” which excludes corporations, REITs, and limited-liability companies (LLCs). From this subsample, I select properties with data populated in the columns for rent and market value. I exclude properties with flags for assisted living or rent control. For 2021, I am able to exclude townhouses; however, for 2018, this column does not exist. These filters leave me with a sample of 601 small landlords in total.

For me to study small landlord costs, the ideal dataset would be a panel of landlord cost components or a cross section of average landlord cost components. The RHFS instead is a snapshot of landlord cost components. Some expenses, such as those for repairs, can be large and irregular. For categories with large and irregular expenses, I average the category as a fraction of rent across landlords instead of using the landlord-level heterogeneity. I provide more details on the construction of this dataset in Appendix A. 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.

II.C Earnings Statements for Public REITs

I use earnings statement supplements to obtain market-level cost components, occupancy, and the number of homes in each market 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. 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. The earnings statement supplements also contain market-level occupancy and rent data.

II.D Census ACS PUMS 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 of residence, household income, and whether the household lives in an owner-occupied, single-family rental, or multifamily rental unit. 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 to2019. 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, such as the median number of rooms in each PUMA, fraction of a PUMA that is single-family housing, median age of housing in a PUMA, fraction of the population with a commute shorter than 45 minutes, fraction of the high-school-aged population enrolled in high school, and fraction of the high-school-aged population enrolled in private school.

II.E Mover-Level 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 of the locations has an address ID, which can be linked to the property dataset. I describe the steps I take to clean this data to construct migration datasets in Appendix A. I validate the moves to and from a given zip code with United States Postal Service (USPS) change-of-address data in Appendix Table A3. I also validate moves from county to county with ACS data in Appendix Table A4. I merge this dataset with the property data on a mover's origin and destination locations to see whether the mover moved into an institutional investor–owned home. I can also observe whether someone lives in an owner-occupied, single-family rental, or multifamily rental unit. I aggregate bilateral migration data between PUMA asset class pairs from 2012 to 2019 to create the migration share dataset to estimate moving costs for the demand estimation. Asset classes describe whether the household lives in an owner-occupied, single-family rental, or multifamily rental unit.

II.F Other Data Sources

I include weather data given the importance of weather as a location amenity, as shown in Saiz (2010) and Chodorow-Reich, Guren and McQuade (2023). Weather data at the county level come from the US Department of Agriculture. I include in the demand estimation as characteristics January sunlight, January temperature, July temperature, and July humidity. I use topography data from Lutz and Sand (2022) at the zip code level. These data describe the fraction of the zip code area unavailable for building because of water, wetlands, or slopes. I use a geospatial join to map the data to census tracts. I create variables for distance to the nearest city and distance to the nearest top-30 city to use in the household demand estimation. 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 TIGERweb 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.

III Description of Institutional Investor Activity

III.A Location Choice and Conversion of Homes to Rentals

I start by describing where the 7 institutional investors studied in this paper purchased homes. Appendix Figure B1 shows the fraction of the total housing stock that the institutional investors own at the county level for the United States. The institutional investors' largest markets are Sunbelt cities that had many foreclosures from 2007 to 2011, including Atlanta, Phoenix, and Tampa. In Paulding County, Georgia, the 7 companies owned 5.7% of all the housing stock as of 2021. I examine the characteristics of the neighborhoods where the institutional investors purchased homes with a descriptive regression where $y_{p,s}$ is a dummy variable if PUMA p in state s has 10 or more institutional investor–owned properties, $X_{p,s}$ is a vector of characteristics describing the housing stock, demographics, and location characteristics, and α_s is state fixed effects:

$$y_{p,s} = \beta X_{p,s} + \alpha_s + \varepsilon_{p,s}. \tag{1}$$

The results in Table B3 show that the institutional investors own properties in PUMAs with low price-to-rent ratios, which make them ideal for conversion of owner-occupied homes to rental units. The institutional investors I study in this paper hold onto these homes to rent, in contrast to iBuyers such as Zillow and Opendoor, which purchased homes to flip, as studied in Buchak, Matvos, Piskorski and Seru (2022) and Raymond (2024).

The institutional investors own properties in regions with steeply upwardly sloped population and job growth pretrends and a high number of foreclosures per housing unit in the great recession. In its initial public offering (IPO) filing, Invitation Homes described how it chooses its markets: "We have 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] American Homes for Rent also targets areas with high population growth: "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] They

[4] INVH form S11, page 4.
[5] AMH form S11, page 7.

also targeted regions with low prices relative to prices before the great recession. Foreclosures were a critical acquisition channel early on, as documented in Mills et al. (2019) and in SEC filings from INVH and AMH. Among the properties that Invitation Homes 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. Additionally, many states have a right of redemption for foreclosures, whereby the homeowner who was foreclosed upon has 12 months after the foreclosure sale to pay the purchaser to recover the property. This right poses a risk for landlords who want to purchase properties to operate as rentals—a risk that can be better absorbed by those with larger diversified portfolios than by operators looking to buy 1 home to then rent. Spatially, the institutional investors purchased homes in rings around cities. They bought homes in PUMAs with higher median household incomes and lower white or college educated shares of the population.

Where they chose to enter the housing market, they amassed concentrated portfolios of housing. In a census tract in Rutherford County, TN, between Nashville and Murfreesboro, these companies own 19% of the entire housing stock: 534 of the 2803 properties in the tract. Figure 1 Panel A shows the fraction of housing stock at the census tract level owned by the 7 institutional investors covered in this paper for the Atlanta metro area. The figure shows that they own up to 10% of all the housing in some tracts surrounding the city. I plot the share of housing stock they own against the share of rental stock they own at the tract level for the whole US in Figure 1 Panel B. In some tracts, the 7 companies combined own 78% of the total rental supply. This implies that institutional investors did some combination of expanding the rental supply and replacing existing landlords.

I compare the physical characteristics of the rentals institutional investors supply compared to other rental units in the same zipcode and owner-occupied housing in the same zipcode. I calculate within zipcode differences between the three groups and average the differences weighted by institutional investors' zipcode level exposure, and then add back the institutional investor mean. Institutional investors supply rental stock that is newer and larger than the other rental stock in the zipcodes they are present in, as shown in Table B4. On average, the institutional investor rental supply is around 7.48 years newer, has 0.23 more bedrooms and 0.16 more baths, and is 20% more likely to be single family than other rentals in the same zipcodes. The institutional investor rental supply is on average 150 sqft smaller than owner-occupied housing, 7.6% smaller. This is consistent with the idea that they bought starter homes.

III.B Trends in Geographies Where Institutional Investors Are Most Concentrated

I analyze the trends associated with institutional investor entry that highlight why there has been so much attention focused on institutional investors. I first show the association between institutional investors' holdings in 2019 with changes in prices and rents at the PUMA level, relative to the rest of the country. Figure B2 Panel A shows this as a binscatter. Institutional investors are assocaited with price increases of up to 40% more than the rest of the US from 2012-2019. They are associated with rent increases of up to 10% more than the rest of the US. The figure also shows how small of a share institutional investors have of a census PUMA. In their most concentrated PUMA, they own 4.5% of the housing. Panel B shows the association with owner occupancy rates. At the PUMA level, there is no trend in the binscatter of owner occupancy rates with institutional investor presence. The owner occupancy rate in the US decreased from 2012–2016, before rebounding to 2012 levels by 2019. Panel C shows the associations of institutional investor entry with household growth from 2012-2019. Panel D shows the associations of institutional investor entry with changes in housing completions relative to the rest of the country. Institutional investors chose areas that realized large increases in population relative to the rest of the country, and large increases in new building supply. The growth in population suggests that factors other than institutional investor entry could have caused prices to rise. The growth in housing completions relative to the rest of the country suggests that the construction response to price and population growth may play a role in these markets and therefore should be modeled.

I explore the possibility that the addition of significant rental supply could have had spillovers on broader rental markets by relieving demand for rentals in other regions. The majority of renters new to institutional investor rentals came from areas with at least some institutional investor exposure, or areas adjacent to institutional investor zipcodes. I examine where people who moved into institutional investor owned homes for the first time came from in Figure B5. The entry of institutional investors increased the rental supply for these renters, and therefore rental demand in their origin zipcodes could have decreased. I examine the association between which origin locations had the most people leave to go to institutional investor homes and the rents in the origin locations. I estimate the following descriptive regression of the change in rent for a zipcode Δr_z in county c from 2012–2021 on indicator variables for the number of people I observe who left that zipcode to move into an institutional investor home for the first time $N_{z,c}$ and control for county level fixed effects:

$$\Delta r_{z,c} = \beta N_{z,c} + \alpha_c + \varepsilon_{z,c}. \tag{2}$$

I plot the results from the descriptive regression in Figure B3. I find that areas where I am able to observe 100 or more people leaving to go to institutional investor homes are associated with rent decreases of 8.4% . When I restrict the sample to origin locations that do not have any institutional investor homes, the association increases, and 10 to 20 people leaving to go to an institutional investor home is associated with a 7.9% decrease in rents from 2012–2021. The association is negative and increases in magnitude with the number of people. It holds for both zipcodes that contain institutional investor homes and those that do not contain any institutional investor homes. The results show that a model of institutional investors' impact must include geographic spillovers to other markets.

III.C Who Moves into Institutional Investor Rentals?

I examine if the rentals that institutional investors supplied increased neighborhood access for the financially constrained. Individual level migration data show where those who moved into institutional investor homes came from. I compare characteristics of the origin locations to the destination locations. I merge tract level data of median incomes, middle school math test scores, and historic economic mobility from Opportunity Insights to both origins and destinations. In Table 1 I show the mean difference in destination tract characteristics relative to origin tract characteristics. 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% increase in likelihood to go to jail, and a 3.4% decrease in likelihood to make it to the top income quintile. To the extent that institutional investors increased the rental supply, they increased it in areas with better schools and economic mobility than the origin locations of those who rent from them.

I compare those who move into institutional investor homes with those who move into other homes in the same tract to better isolate whether institutional investors are not just increasing the quantity of rentals in good locations, but also changing the flow of people to these good locations. Among all movers into tracts with institutional investor homes, I create a dummy variable for those who moved into a institutional investor home for the first time and run a regression of origin tract characteristics on the dummy variable, with destination tract fixed effects. Results are in Table 2. Those who moved into institutional investor homes came from worse areas than those who moved into other homes in the same census tract, suggesting that institutional investors increase access to the neighborhood for those who come from worse areas.

III.D Differences Between Small and Large Landlords

To figure out if institutional investors affect the housing market, we need to understand how they are different from existing single family landlords and how these differences might matter to the housing market. I start by providing some background information about operator size distributions in the single family rental market in February of 2021 by constructing operator level single family rental portfolios from Verisk property data. Figure 2 Panel A shows the fraction of all single family rental homes owned by operators of different sizes. It also shows how many of the operators within a size bucket operate in only one county as opposed to multiple counties. Institutional investors entered an extremely fragmented market dominated by tiny "mom and pop" landlords. 71% of single family rentals are owned by operators with 1-3 properties. 75% of single family rentals are owned by operators who do not operate in multiple counties. Institutional investors, even in 2021, make up only 1.8% of single family rentals. However, as shown earlier in Figure 1 Panels A and B, their spatial concentration makes them relevant operators in the regions where they are located. In this fragmented market, institutional investors are much larger, where some own over 80,000 homes. This allows them to have spatial concentration, which is not something that is possible for operators with 1-3 homes.

Next, I examine how economies of scale lower institutional investor landlord operating costs relative to small landlords. Figure 2 Panel B compares cost components for average small landlords from the Rental Housing Finance Survey, to cost components from earnings statements for Invitation Homes and American Homes for Rent which I call the large average. Institutional investors have lower property taxes as a share of rent. This may be due to the fact that institutional investors are more likely to appeal their property tax assessment valuations, as documented in Austin (2022). Institutional investors also have lower operating expenditures. In American Homes for Rent's IPO filing, they mention that they get quantity discounts for materials regularly used including paint, flooring, and blinds. Invitation Homes in its IPO mentions that it is able to get discounts for HVAC systems and discounts for contractors by working directly with vendors, for the work that it does not use in house staff for. Large landlords have much lower insurance costs, 1-2% of rent rather than 5-6%. Large operators bargain with insurance companies for a bulk discount here as well. While in Figure 2 Panel B it appears that large landlords pay more in management costs, that is because 83% of small landlords do not hire any 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 towards their internal management operations. While I am not able to break this out in the data, institutional investors also have vertically integrated leasing and acquisition teams. American Homes for Rent, before internalizing its acquisition team, paid a 5% fee on top of all closing costs for each acquisition, which suggests that they may have saved some of this 5% through the acquisition. Overall, institutional investors benefit from economies of scale that lower operating costs.

Large and small landlords also look very different on the financing side. 63% of small landlords do not have mortgages or similar debt in the RHFS. I verify this number in Verisk and find that 57% of small landlords here do not have a mortgage. Large landlords have higher levels of debt. In 2021, Invitation Homes had a debt to value ratio of 51% and American Homes for Rent had one of 33%. They use many types of debt including asset backed securitizations, bonds, term loans and credit lines. I show differences in interest rates for small landlords, owner occupied homes, and the weighted average interest rates on debt for INVH and AMH in Figure B6. There is a spread between new mortgages for owner occupants and small landlords of around 0.2%. The spread is larger for existing mortgages, around 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.

Small landlords minimize costs in a way that does not scale, suggesting that they have decreasing returns to scale. 83% of small landlords do not use any professional manager and 63% do not have a mortgage. At a certain scale, debt and managers are necessary because people have limited equity and as the number of properties increases, it gets harder for a person to manage them alone. 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 that has a mortgage. High cost small landlords are much more likely to have a mortgage than low cost small landlords. Therefore, a move from no mortgage to a mortgage would likely move a small landlord to a higher cost portion of the histogram, suggesting decreasing returns to scale. Additionally, small landlords who purchased homes recently are more likely to have a mortgage than those who purchased decades ago. I show this in Figure B7 Panel A, which buckets landlords in the RHFS 2021 vintage by when they purchased a home, and shows the fraction of that bucket that has a mortgage. Panel B shows the fraction of an original mortgage balance remaining by purchase year for those who still have mortgages. Small landlords appear to get mortgages of around 80% LTV, similar to households, and then pay them off over time. These pattern suggests that small landlords who want to change the number of units they operate are more likely to have a mortgage than those who have operated a property for 20 years, and are more likely to have higher mortgage balances, and therefore have higher interest expenses suggesting decreasing returns to scale within operator. Additionally, mortgage underwriting liquid reserve requirements by Fannie Mae increase for additional investment properties up to 10, so financing constraints increase with the number of properties at the size range relevant to the majority of single family operators.[6]

Large landlords appear to have better returns to scale. While there is no data on INVH's and AMH's costs before they went public, I can examine how changes in scale affect cash costs after they became public companies. First I examine market level average operating expenses per home for INVH in Figure B8. The figure shows market average operating expenses per home against the market average number of homes. There is no pattern between the number of homes and the operating expense per home. I examine variation in portfolio size due to a merger to get a different look at how operating expenditures per home might vary with portfolio size. In 2017, Invitation Homes bought Starwood Waypoint Homes and went from 50,000 homes to 82,000 homes. I plot the change in operating expenses per home against the change in number of homes from this merger for each market in Figure 3 Panel B. The black dotted line represents no change in operating expenses per home. While this is not exogenous variation, it is strongly suggestive that these companies can almost double the number of homes they have in a market without raising operating costs per home. I am able to examine variation in costs only after these companies have already accumulated large portfolios. Most likely, these companies early on experience increasing returns to scale as they are paying fixed costs to build capabilities for management, acquisition, and renovation. Then, they have constant returns to scale, and then decreasing returns to scale. The variation I observe suggests constant returns to scale are a reasonable assumption for the the number of homes in the range around the merger quantities, which is the relevant region for model simulations.

[6] Fannie Mae minimum reserve requirements

III.E Stylized Model of Supply and Demand for Single-Family Rentals

Now that I have established that small landlords have decreasing returns to scale and large landlords have constant returns to scale over a large range of quantities, I use these facts in a stylized model of the single family rental market to illustrate economic channels through which institutional investors can affect the housing market. Figure 4 Panel A shows the supply and demand curves for single family rentals in one region. Households have downward sloping demand, small landlords have upward sloping supply, and large landlords have constant supply, as motivated by the earlier section. Here, if the large landlords choose competitive quantities, the equilibrium moves to the right from A to B, and rent decreases and the number of rentals in the region increases.

To illustrate the market power channel in this stylized example, I assume there is only one large landlord. This large landlord can supply a significant amount of demand that small landlords cannot, and therefore is a monopolist over the residual demand. A profit maximizing large landlord therefore can internalize the impact its quantity choice has on rent, leading to market power. I this show in Figure 4 Panel B. The large landlord chooses a quantity where the residual marginal revenue intersects its cost curve. This shifts the equilibrium left to C, and raises rents and lowers quantities. The movement from B to C is the effect of market power, which is derived from the cost advantage of the institutional investors. This cost advantage is derived from scale and spatial concentration.

Institutional investor entry could increase rents if their entry increased small landlord costs by enough that the quantity of rentals would on net decrease. In the graph, this would be a shift in small landlord supply to the left far enough that C would be to the left of A. Institutional investor entry does raise costs for small landlords because institutional demand for owning homes raises prices, which increases property tax expenses and the opportunity cost of holding wealth in real estate. Whether this curve shifts to the left by enough to result in a net increase in rent and decrease in rentals will be examined in the quantitative model in the next section.

Supply and demand for single family rentals are modeled as a Cournot (Cournot, 1838) oligopoly where small landlords are price takers and large landlords choose quantities to maximize prices. Two features of single family rental market make Cournot fitting for this setting. First, single family rentals are highly liquid relative to other real estate assets. It's easier to sell a piece of a single family portfolio than a piece of a multifamily portfolio because the discrete units are smaller. Also, institutional investors can sell to both households and landlords, providing an additional source of exit liquidity. So rather than raising rents and increasing vacancies, an institutional landlord would sell the vacant units or not have bought them in the first place. There are no barriers to entry: if an institutional investor sells a home, another landlord could operate it if its profitable. If rents rise sufficiently, a small landlord could buy a home from a large landlord or a homeowner and then offer it as a rental. Both the liquidity and the lack of a barrier to entry make single family rentals make Cournot an ideal way to model the market. This is in contrast to market power in multifamily housing, where there is a tradeoff between rents and vacancy due to the inability of large landlords to sell units within a building and to sell to households.

IV Model

To estimate the equilibrium impact of institutional investors, I add to the stylized model an integrated rental and ownership market, construction, and multiple regions at the census PUMA level where households can move to and from. The model has four agents. Households decide where to live and whether to own or rent by solving a discrete choice problem. Small landlords decide whether to operate or not by comparing expected operating cash flows to the amount of cash they would get from selling their properties. In aggregate, they have decreasing returns to scale, as motivated by the previous section. Large landlords choose a number of rentals in each region to operate. They are large enough that they internalize the impact of their quantity choices on equilibrium rent and prices when maximizing profits, and are therefore modeled as Cournot oligopolists. An aggregate builder increases the number of homes in a region when prices increase.

The model provides four key benefits. First, it allows me to answer quantitative questions, such as, how many households would own homes if the institutional investors did not enter the market? A household who sells a home or decides not to buy in a region when prices rise can buy a home in a different region, where supply can also respond. A local estimate of the impact of institutional investors on homeownership that does not include this household would overstate the impact. Second, I can compare economic channels to see what drives net effects. This is important because natural experiments in mergers isolate only the part of institutional investor impact on rents that is due to increasing ownership concentration, and we want to know the net effect of institutional investors on rents. Third, the model can quantify economic channels to estimate, for example, how much larger the impact on prices would have been if there were no construction response. Fourth, the model allows for policy simulation.

The model, by construction, excludes un-modeled mechanisms. This helps in isolating the impact of institutional investors because it excludes the population increases that occurred in institutional investor PUMAs that were unrelated to institutional investor entry that may have affected prices and rents. However, it excludes possible mechanisms for investor impact like if the institutional investors change the quality of homes or of the neighborhood. For example, if institutional investors renovate properties, this could increase demand for these properties and therefore increase rents. If rents rise due to renovations, it's not clear that that is negative for renters, as opposed to market power where quantities decrease and rents increase with no change in the quality of rentals. There's mixed evidence on the effect of institutional investors on neighborhood crime. Gurun et al. (2023) shows that a merger between institutional investors decreases crime, while Billings and Soliman (2023) shows that areas where institutional investors purchase homes experience an increase in crime. Whether or not institutional investors change local amenities for homeowners in not central to the questions I study in this paper: whether they decrease the number of homes available for owner occupancy, whether their market power causes a net increase in rents, and how they affected market level prices and rents. I would expect impacts of amenity changes to be small at the PUMA level due to the overall low institutional investor PUMA ownership share.

IV.A Housing Demand

The estimation of household demand allows me to measure how many households leave a PUMA if prices increase, where they go to, and whether they become homeowners or renters in the destination location. Households solve a discrete choice problem of where to live and whether to own, rent single family, or rent multifamily in that location. The discrete choice model is similar to models from McFadden (1978), Bayer et al. (2003), Bayer et al. (2007), Diamond (2016), Schubert (2021), Calder-Wang (2022), and Almagro and Dominguez-Iino (2024) for housing and Koijen and Yogo (2019), Koijen and Yogo (2019b), Koijen et al. (2023), and Jiang et al. (2023) for financial markets. Households are heterogeneous in income, denoted by income group level h, and origin location i. Income heterogeneity allows for heterogeneity in price and rent elasticities. Origin location heterogeneity allows for realistic spatial substitution patterns.

A household from origin location i in income group h in asset class l, where asset classes are owning, renting single family, or renting multifamily, solves a discrete choice problem to figure out where to move, j, which could also be not-moving if $j = i$, and whether to own, rent single family, or rent multifamily in that destination, k. The household maximizes utility based on characteristics of the destination location and asset class, $X_{j,k}$, and a moving utility cost from location i asset class l to location j asset class k: $\tau_{(i,l)\to(j,k)}$. The asset class in location j has a log price of $p_{j,k}$, which is the log of the purchase price of owner occupied homes if $k = \textit{owneroccupied}$, of single family rent if $k = rent_{sf}$, or of multifamily rent if $k = rent_{mf}$. A region asset class has unobservable quality $\xi_{h,j,k}$, and households have a latent demand denoted by $\varepsilon_{h,(i,l)\to(j,k)}$. A household's indirect utility for moving from (i,l) to (j,k) is based on these characteristics and their corresponding elasticities β as follows:

$$u_{h,(i,l)\to(j,k)} = \beta_{h,k,0}p_{j,k} + \beta_{h,k,d}X_{j,k} + \tau_{(i,l)\to(j,k)} + \xi_{h,j,k} + \varepsilon_{h,(i,l)\to(j,k)}. \tag{3}$$

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

$$w_{h,j,k} = \sum_{i,l} \frac{\exp(u_{h,(i,l)\to(j,k)})}{1 + \sum_{(m,s)} \exp(u_{h,(i,l)\to(m,s)})} w_{h,i,l}. \tag{4}$$

$X_{j,k}$ include characteristics related to climate (January temperature, January sunlight, July temperature, July humidity), 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 high school age population in high school, fraction of high school age population in private school), topography (the average amount of land within 3 miles unavailable to build on because of water, wetlands, and total unavailable land), and a year fixed effect. All of these are interacted with a dummy variable for whether the destination asset class is owner occupied housing or a rental, to allow for different coefficients across asset classes for the same characteristic. Households can also migrate to an outside asset. The outside asset in the model is any PUMA or asset class that is missing an $X_{j,k}$ but has a price or rent, any PUMA where the median house value is below $90k, any PUMA where the monthly median contract rent is below $200, or any PUMA where the median age of the housing stock is 1939 or earlier.

To get accurate geographic substitution, each income group has within group heterogeneity by origin location. Each origin asset class and destination asset class pair has a different utility "cost" of moving: $\tau_{(i,l)\rightarrow(j,k)}$. This is a function of pairwise distance, the number of social connections from Meta's Social Connectedness Index (SCI) as used in Bailey, Cao, Kuchler and Stroebel (2018), as well as a dummy variable for all possible transitions between owning, renting single family, or renting multifamily interacted with a dummy variable for whether one stays in the same PUMA. The next section will provide more details on the estimation of this moving cost.

Heterogeneous moving costs result in the propagation of the institutional investor impact along a network based on empirical moving patterns, similar to how housing market shocks are propagated along search networks in Piazzesi, Schneider and Stroebel (2020). Diamond (2016) models household demand with birth state heterogeneity. Dynamic housing models estimated directly from migration data like those in Schubert (2021) and Almagro and Dominguez-Iino (2024) get accurate spatial substitution for free by estimating migration shares as a function of characteristics for different household types. The method in this paper combines migration data that does not have heterogeneity in household types, with cross sectional location data that does have heterogeneity in income, to get realistic spatial substitution in a static model with heterogeneous households.

Portfolio weights for each household group sum to 1:

$$\sum_{(i,l)} w_{h,i,l} = 1. \tag{5}$$

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

$$Q_{d,households,i,l} = \sum_{h} w_{h,i,l} N_h. \tag{6}$$

IV.B Small Landlord Demand

Small landlords react to changes in rents and prices, therefore their demand for owning homes to rent adjusts when institutional investors enter the housing market. Each region j has a stock of small landlords, $N_{small,j}$. A small landlord i in region j operates if cash flows from operating are preferred to selling:

$$E\left[\sum_{t} \frac{(R_{j,t} - C_{i,j,t})}{(1+r_e)^t}\right] \geq P_{j,t} \times (1 - BrokerFee) - M_{i,j,t}. \tag{7}$$

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 get from selling a home. The landlord gets the purchase price $P_{j,t}$ minus a broker fee, and then has to pay back a mortgage $M_{i,j,t}$. 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 growth and job growth in the region, as well as state level trends. The cost for a landlord i in a region j is:

$$C_{i,j} = P_j \times PropTax_j + InterestExpense_{i,j} + OtherCosts_i + R_j \times ManagerFee_i. \tag{8}$$

I show that small landlords in the RHFS pay off their mortgages over time in Figure B7. Panel A shows that the fraction of small landlords with mortgages decreases with time from purchase. Panel B shows that the mortgage balance outstanding as a fraction of the original mortgage amount, among those who still have mortgages, decreases with time from purchase. Panel C shows that most small landlords with mortgages have term lengths of 30 years. I therefore assume in the model that the typical small landlord has a 30 year mortgage that they pay off over 30 years, and is aware of this expected payoff behavior and takes this into account when deciding whether to operate or not. This allows 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 landlord 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:x

$$R_j \geq (r_e - g_j) \times (P_j \times (1 - BrokerFee) - M_{i,j,t}) + C_{i,j}. \tag{9}$$

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

$$Q_{d,small,j} = \sum_{i \in N_{small,j}} I\left[R_{j,t} \geq (r_e - g_j) \times (P_{j,t} \times (1 - BrokerFee) - M_{i,j,t}) + C_{i,j,t}\right]. \tag{10}$$

At each rent, for a given price, a certain number of these individual landlords will decide to operate or not operate. The number is increasing in rent and decreasing in price. The aggregate small landlord has decreasing returns to scale due to the heterogeneity in costs of the underlying individual landlords. The heterogeneity in costs that leads to this decreasing returns to scale is driven by different interest expenses and operating expenses.

IV.C INSTITUTIONAL INVESTOR DEMAND

I model large landlord demand for homes in a region, rather than set demand to equal observed quantities in the data, to get demand that varies with parameters and market structure. This allows for the modeling of large landlord demand changes due to mergers or rent increase limits. A large landlord i chooses a quantity of homes to buy in region j, $Q_{i,j}$, to maximize profits subject to a required cash margin:

$$\max_{Q_i} \{Q_i \times (CashFromOperating - CashToBuy), 0\} \tag{11}$$

$$s.t. \ \frac{Rent - Cost}{Cost} \geq 30\%.$$

Both Invitation Homes and American Homes for rent have cash margins of around 30% in each market after subtracting company level cash costs like interest, management, and general administrative costs from market level operating margins.

Large landlords buy and renovate a given home to receive operating cash flows. They are modeled as Cournot oligpolists who internalize the impact of Q_i on rents and prices given the quantities of others in the market, Q_{other}, which includes small landlords and other large landlords. They purchase each home with debt D_t that is equal to the company level debt to value ratio times the price of the property:

$$CashFromOperating = E\left[\sum_t \left(\frac{R_{j,t}(Q_{other} + Q_i) - C_{i,j,t}}{(1+r_e)^t}\right)\right] \tag{12}$$

$$CashToBuy = P_{j,t}(Q_{other} + Q_i) \times (1 + renovationCost) - D_t \tag{13}$$

$$C_{i,j} = P_j(Q_{other} + Q_i) \times PropTax_j + IntExp_i + OtherCosts_{i,j} + ManagementCosts_i. \tag{14}$$

Region specific costs depend on the local property tax rate. They have region specific operating costs that are a function of local contractor wages. Unlike small landlords, their interest expense and management costs are not region specific.

Large landlords have the same expected cash flow growth rate as small landlords, g_j, which allows one to model their cash flows as a growing perpetuity. Policies that set a rent growth limit for large landlords will cap g_j for large landlords but not small landlords.

This mechanism for market power here is different from that in multifamily housing. For multifamily housing, market power results in a trade-off between raising rents and lowering occupancy, as in Calder-Wang and Kim (2024) and Watson and Ziv (2024). Because single family homes are more liquid, if the institutional investors want to lower quantity, they can sell the homes rather than leave them vacant, or not buy the homes in the first place. Single family homes are more liquid than multifamily homes for two reasons: they are smaller so one can sell part of a portfolio more easily, and one can sell to both landlords and homeowners. I show the occupancy rates for Invitation Homes' markets in Figure B4. Occupancy rates fluctuate here by up to 4% from 95% to 99%. They increase sharply after the onset of the COVID-19 pandemic, when many people moved out of cities as documented in Gupta, Mittal, Peeters and Van Nieuwerburgh (2022) and Coven, Gupta and Yao (2023). They do not change substantially around the date of the merger when Invitation Homes bought Starwood Waypoint Homes. High occupancy rates that move due to trends unrelated to mergers, coupled with the difference in liquidity between single family and multifamily homes, suggest the mechanism for market power here is not raising rents and increasing vacancy. Instead, a company can maximize profits by selling homes or not buying too many homes to keep rents high.

IV.D 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:

$$\log\left(\frac{Q_{j,own,new}}{Q_{j,own,2012}}\right) = \max\left\{\gamma_j \times \log\left(\frac{P_{j,own,new}}{P_{j,own,2012}}\right), 1\right\}. \tag{15}$$

The housing supply cannot shrink if prices go down. Landlords or homeowners can buy these units.

For γ_j, I use new unit supply elasticities with repsect to price from Baum-Snow and Han (2024), who provide publicly available tract level elasticities. I aggregate the elasticities to get PUMA level γ_j. Baum-Snow and Han (2024) estimate the elasticities with a finite mixture model IV that is a function of 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 due to topography, and the metro area 2005 Wharton Residential Land Use and Regulation Index. The model uses a Bartik shock as an instrument for price changes that is constructed from variation in labor demand shocks to commuting destinations. Elasticities are higher farther from city centers, where more land is flat, and where regulation is less restrictive.

The quantity rentals in each region is determined by the demand of small and large landlords:

$$Q_{s,rent} = Q_{d,smalllandlords} + Q_{d,largelandlords}. \tag{16}$$

There is a multifamily rental asset class in the model that has perfectly inelastic supply.

IV.E Market Clearing

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

$$\mathbf{p} = f(\mathbf{p}) = \log\left(\mathbf{P}\cdot\left(\mathbf{Q}_{d,\text{households}} + \mathbf{Q}_{d,\text{smalllandlords}} + \mathbf{Q}_{d,\text{largelandlords}}\right)\right) - \log(\mathbf{Q}_s). \tag{17}$$

For rentals, $Q_{d,largelandlords} = Q_{d,smalllandlords} = 0$ because landlords can own properties and cannot rent them 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 describe how to compute counterfactual prices in Appendix C.

V Estimation

V.A Household Demand

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

Step 1: Migration costs. First I estimate $\tau_{(i,l)\to(j,k)}$ by examining the role of distance, social connectedness, and asset class transitions in bilateral migration data. 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 can be equal to each other, and l and k are asset classes and can also be equal. The dataset constructs migration shares for the all movers and non-movers from 2012–2019. Each row is an origin destination pair. Full details for the construction of this dataset are in Appendix A. I model migration shares to be based on characteristics of the destination, $X_{j,k}$, log price if k is owner occupied, $p_{j,k}$, log rent if k is a rental, $r_{j,k}$, and origin destination pair characteristics $T_{(i,l)\to(j,k)}$:

$$w_{(i,l)\to(j,k)} = \beta_p p_{j,k} + \beta_r r_{j,k} + \beta_{x,k} X_{j,k} + \beta_t T_{(i,l)\to(j,k)} + \varepsilon_{(i,l)\to(j,k)}. \tag{18}$$

Origin destination pair characteristics $T_{(i,l)\to(j,k)}$ include distance, the social connectedness index for the pair of PUMAs, and interactions between all possible asset class transitions and a same PUMA indicator variable. Destination characteristics are the same in the estimation of migration costs and in household demand which are detailed in the previous section. I estimate (18) on the intensive margin with linear IV. Details on the instruments will follow the description of step 2 because both steps use the same instruments. I recover estimates for β_t and use those to create the moving costs in utility terms:

$$\hat{\tau}_{(i,l)\to(j,k)} = \beta_t T_{(i,l)\to(j,k)}. \tag{19}$$

Step 2: Household demand. Once the $\hat{\tau}_{(i,l)\to(j,k)}$ have been estimated, I partition the right hand side of (3) into two terms:

$$u_{h,(i,l)\to(j,k)} = \delta_{h,j,k} + \hat{\tau}_{(i,l)\to(j,k)}. \tag{20}$$

Equation (4) becomes:

$$w_{h,j,k} = \sum_{i,l} \frac{\exp(\delta_{h,j,k} + \hat{\tau}_{(i,l)\to(j,k)})}{1 + \sum_{(m,s)} \exp(\delta_{h,m,s} + \hat{\tau}_{(i,l)\to(m,s)})} w_{h,i,l}. \tag{21}$$

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:

$$\hat{\delta}_{h,j,k} = \beta_{h,p} p_{j,k} + \beta_{h,r} r_{j,k} + \beta_{h,x,k} X_{j,k} + \xi_{h,j,k} + \varepsilon_{h,(i,l)\to(j,k)}. \tag{22}$$

I constrain $\beta_{h,p}, \ \beta_{h,r} < 0$ to ensure 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 co-varying with something desirable to households that is outside of the model. I estimate 22 separately for each income group for the panel of yearly housing holdings from 2012–2019 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 both (18) and (22) with linear IV. $p_{i,l}$ and $r_{i,l}$ may be correlated with $\varepsilon_{(i,l)\to(j,k)}$ and $\varepsilon_{h,(i,l)\to(j,k)}$. When price and rent are positively correlated with latent demand, this can bias elasticities upwards. I instrument for the prices and rents in a PUMA with features of the housing stock and topography of neighboring regions, similar to Bayer et al. (2003), Bayer et al. (2007), and Calder-Wang (2022). The identification assumptions are that for a given PUMA's price and rent, characteristics of neighboring regions matter through a competition channel. But these neighboring PUMAs' characteristics do not affect the utility of one living in that PUMA because they are sufficiently far away, when controlling for own region characteristics.

For 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 land unavailability measures at the zipcode level from Lutz and Sand (2022), which describe how much water is in each zipcode, how much of the zipcode is covered by wetlands, and the overall unavailability of land in a zipcode due to topography which also includes slope. To map the zipcode measure to census PUMAs, 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 zipcode 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 up to the PUMA level. This results in a measure for a PUMA that is the average unavailability for each house in the PUMA within 3 miles, and in a 3-10 mile ring away. I use three other instruments that are average values of housing stock characteristics of neighboring PUMAs: the median age of the housing stock, the median number of bedrooms per home, and the fraction of the regions that is single family housing.

I show the first stage of the IV regression of Equation (22) in Appendix Table B6. F statistics for the instruments are 1000.2 for log(price) and 1630.6 for log(rent). For log rents, all three topography features for within 3 miles have opposite signs to the corresponding features for the 3-10 mile ring. Higher land unavailability in neighboring regions is associated with higher rents, illustrating the competition channel where if it is harder to build nearby, rents would be higher. For log prices, land unavailability due to water for neighboring regions increases price and is of the opposite sign to land unavailability due to water within 3 miles. The statistical significance and the opposite signs suggest that characteristics for neighboring regions are relevant, and affect price and rent through a different channel than the PUMA's characteristics affect price and rent.

I examine the instrument spatially in Figure B14. Panel A shows the mean land unavailability due to water within 3 miles for each PUMA in Georgia, Panel B shows the mean land unavailability due to water 3-10 miles away, Panel C shows the difference between Panel B and Panel A, and Panel D shows log house prices in each PUMA. PUMAs near the city center have more land unavailability due to water in neighboring regions than in their own region. This appears to be correlated with housing prices, which could suggest that land in the city center has high prices because it is harder to build nearby. An alternative hypothesis for this correlation in the regression for the whole US could be that cities occur near ports but on land that one can build on, but close to land that one cannot build on due to water, and that these ports drive higher house prices and rents. I control for distance to city center in these regressions, so the differential impact of neighboring topography relative to own topography on prices and rents must remain after controlling for proximity to city centers.

Estimation results. Table B5 shows the estimation results for equation (18). People are more likely to move to nearby PUMAs with a large social connectedness index than farther away PUMAs with fewer social connections. People are most likely to stay within the same asset class and within the same PUMA.

Figure B9 shows the moving elasticities for each income group with respect to prices and rents from estimating equation (22). There is substantial variation in moving elasticities with respect to prices and rents by income group. For both purchasing housing and renting, elasticity decreases with income. These elasticities are the percentage of a group that will leave to go to a different PUMA, not the percentage that will leave a house. The model abstracts away from downgrading within a PUMA. Someone who stays in the same PUMA but downgrades when faced with a price shock would be recorded as inelastic here because these are moving elasticities, and to different PUMAs. Therefore the elasticities will be lower than housing unit elasticities. I expect that as the geography size increases, the elasticity of a group to that geography's housing prices decreases. For example, it's easier to leave a neighborhood if neighborhood prices increase than leave the country if the country's prices increase. Around 80% of counties in the US have a population less than the minimum PUMA population,[7] therefore a person leaving the PUMA would be a larger move than a person leaving their county for the majority of PUMAs in the US. The moving elasticities are sufficient to study the question of how institutional investors increased the prices in an entire PUMA. Functionally, low moving elasticities for high income groups mean that in the model, when large landlords shock the market, those making 100k+ will not leave to go to a different PUMA.

V.B Small Landlord Demand

I calibrate the small landlord demand for each region in equation (10) by sampling from distributions of small landlord operating costs and mortgage balances. I sample $N_{small,j}$ times from the distributions, where $N_{small,j}$ is the number of single family rentals in region j in 2012. I repeat equation (10) here for convenience:

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

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

Region-specific parameters. Each small landlord in a given PUMA pays the same property tax rate $PropTax_j$. The property tax rate comes 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 can observe small landlord mortgage origination amounts. I use the November 2015 data and select properties purchased in 2012 or earlier, because November 2015 is the earliest cross section of

[7] https://www.census.gov/library/stories/2017/10/big-and-small-counties.html.

property data in the dataset. I calculate mortgage balances outstanding by assuming 30 year terms and linear amortization. This gives me an empirical distribution of mortgage balances for each PUMA. From this, I can calculate the interest expense which is the perpetuity equivalent of the present value of interest payments. For interest payments, I use the median small landlord interest rate of 5.25% from the mortgages in this distribution. Full details are described in Appendix A. I plot a histogram of PUMA level average mortgage balance outstanding as a percentage of sale price in Figure B11. There is significant regional heterogeneity in small landlord leverage. I plot the same histogram of PUMAs for regions where institutional investors purchased more than 100 homes. Institutional investors entered PUMAs with relatively high 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 2006–2012 at the PUMA level on an indicator variable for above median national population growth from 2006–2012, an indicator variable for above median annual job growth from 2004–2013 from the Opportunity Insights data, and state fixed effects:

$$g_{j,s} = \beta_{pop} I\left[\Delta pop_{j,s} \geq Med.\Delta jobs_{j,s}\right] + \beta_{jobs} I\left[\Delta jobs_{j,s} \geq Med.\Delta jobs_{j,s}\right] + \alpha_s + \varepsilon_{j,s}. \quad (23)$$

I recover the $\beta_{pop} I\left[\Delta pop_{j,s} \geq Med.\Delta jobs_{j,s}\right]$, $\beta_{jobs} I\left[\Delta jobs_{j,s} \geq Med.\Delta jobs_{j,s}\right]$, and α_s for each PUMA and then set the mean of this resulting distribution to be the 5 year expected rent growth from the NY Fed's SCE data in 2014, which is the earliest year of publicly available SCE data, which is 4%. This process results in an estimation for expected rent growth that is the sum of mean expected rent growth nationally, plus a rough PUMA level adjustment for how much population growth, job growth, and state level trends contributed to rent growth in the past. Landlords assume that a PUMA above the median in each category will continue to be above the median, and that the relationship of this with rent stays the same, as well as state level trends to be the same. Both small and large landlords have the same expected rent growth. I show the expected rent growth for Georgia in Figure B10. The range for Georgia is 1.8%–5.7%.

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 A. For each PUMAs small landlords, I sample from this distribution the operating costs excluding interest and property taxes $N_{small,j}$ times to get that PUMAs landlords' operating costs and manager fees as a function of region specific rent. I set *BrokerFee* to be 6% for all PUMAs, which is standard.[8]

To get r_e, the I assume that small landlords have the same asset betas as INVH and AMH from their IPOs to 2024, and set their required rate of return to if they had zero leverage. I get this from applying the CAPM to the un-levered 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. We can see this in the RHFS in that some small landlords have 0 or negative cash flows, and some have less than the risk-free rate, even if we exclude interest expense. If we excluded all interest expense and set the discount rate to 0, there would still be some landlords who are unprofitable. Including interest expenses and considering the opportunity cost of money tied up in the property make it so that a larger number of landlords in the data should not be operating, but are operating.

Estimation results. To measure the fit of the small landlord estimation procedure, I estimate small landlord demand with observed 2012 rents and prices and compare estimated small landlord quantities with actual quantities. I compare the quantities in Georgia and in the PUMAs within Georgia where institutional investors combined own over 1000 homes, and call these regions "High Investor Activity." Results are in Table B1. Estimated quantities are highly correlated with actual quantities. The estimation underestimates quantities in both Georgia and in the subset of Georgia where institutional investors are most active. The estimation performs better in regions with high institutional investor activity. Overall, the model can't explain why all small landlords operate. This is because there are a number of small landlords who are unprofitable in the RHFS data, which I use in this calibration. If I took observed small landlord costs and dropped interest expense entirely and used a discount rate of 0, there are landlords who should not be operating. So it is not surprising that this estimation underestimates the landlords who operate. The estimation performs better where rent to price ratios are high. There are a few reasons why small landlords might have an propensity to be landlords above and beyond the financial returns when compared to other financial assets. First, they have option value to use the home for personal use some day. Second, they have control rights. Third, if

[8] https://listwithclever.com/average-real-estate-commission-rate/

a large number of small landlords are retirees, they might value stable cash flows more than the CAPM would suggest. I make up for this underestimate by inserting a residual so that the model matches the 2012 housing market exactly:

$$Q_{d,small,j} = \sum_{i \in N_{small,j}} I\left[R_{j,t} \geq (r_e - g_j) \times (P_{j,t} \times (1 - BrokerFee) - M_{i,j,t}) + C_{i,j,t}\right] + \Xi_j. \tag{24}$$

What matters for the model is not the quantity of the underestimate (because the residual makes up for this), but the slope of the supply curve where it intersects demand. Differences in elasticities between PUMAs with high investor activity where the estimation performs better are not too far from elasticities in all of Georgia, and are more relevant to the model counterfactuals.

I examine the fitted elasticities as a function of parameters in the calibration with a regression in Table B2. With the estimated quantities for small landlords in each PUMA in Georgia, I raise housing prices by 1% to measure the elasticity with respect to price. High expected rent growth decreases the sensitivity of small landlords to price increases. High price to rent ratios and high PUMA leverage increase the sensitivity of small landlords to price increases. Low price to rent ratios and high expected rent growth lead to institutional investor PUMAs containing small landlords who are less sensitive to price increases than in other parts of Georgia.

V.C Large Landlord Demand

I calibrate large landlord demand for each region using cost data from earnings statement supplements. I repeat equation (12) for convenience:

$$\begin{aligned}
CashFromOperating &= E\left[\sum_t \left(\frac{R_{j,t}(Q_{other} + Q_i) - C_{i,j,t}}{(1 + r_e)^t}\right)\right] \\
CashToBuy &= P_{j,t}(Q_{other} + Q_i) \times (1 + renovationCost) - D_t \\
C_{i,j} &= P_j(Q_{other} + Q_i) \times PropTax_j + IntExp_i + OtherCosts_{i,j} + ManagementCosts_i.
\end{aligned}$$

Prices, rents, 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 American Homes for Rent's 2014Q1 average market cost and subtract property taxes. This is the earliest period for which 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. State level contractor wages come from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages. I use a renovation cost of 20%, taken from AMH's IPO filings where they detailed the cash spent on acquiring new homes and the amount of that cash that went to renovations and closing costs. For the debt fraction, I use a 65% debt to value for INVH's early time periods. r_e is calculated with the CAPM using total return betas for INVH and AMH from their IPO's to the 2024, with INVH's early debt to value ratio, the 10 year treasury rate as of 2012 which was 2%, and a market equity premium of 6%. Given the importance of foreclosures in where large landlords purchased homes, I allow large landlords to purchase homes only in the top 50%-ile of PUMAs in the number of foreclosures per unit from 2007-2011.

I show the large landlord estimation results spatially in Figure B12. Panel A shows the estimated quantities for 3 identical large landlords and Panel B shows the actual quantities for institutional investors in 2019. I choose 3 large landlords to enter because that is the mean number of large landlords in any one PUMA where institutional investors have significant presence. The spatial pattern is similar for both the estimated and the actual. The total number of units in Georgia is 26k for the estimation and 22k for the actual. The model over predicts entry in regions with high rent to price ratios but low foreclosures.

V.D Housing Supply

For the supply side, I use the 2011 estimates of new unit supply elasticities from Baum-Snow and Han (2024). I aggregate tract level elasticities to the PUMA level to get γ_j. First I map census tract identifiers from the 2000 version of census geographies to the 2010 census geographies. Elasticities are then aggregated to the PUMA level with a weighted average by the number of homes in each tract. This results in a supply elasticity that is heterogeneous in each PUMA, which depends on the elasticities in the tracts that make up the PUMAs. I show the supply elasticities for new units for Georgia in Figure B13. Missing supply elasticities are imputed with state level means. The mean for Georgia is 0.22. Most PUMAs with missing values are not in areas where institutional investors entered.

VI Impact of Institutional Investor Entry

VI.A 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. In 2021, the mean number of institutional investors in a PUMA where the investors have at least 10 units each is 3. I implement the Newton step algorithm from Koijen and Yogo (2019) described in Appendix C to recover market clearing prices, rents, and quantities.

I begin by analyzing the impact of institutional investors on the number of homes available for homeownership. Institutional investors decreased the housing available for owner occupancy by 23% of the homes they purchased. The impact of the investors on homeownership is significantly less than 1:1 because of two supply responses. I show the impact on homeownership and the supply responses in Figure 5 Panel A. When an institutional investor purchases a home, that puts downward pressure on the number of homes for owner occupancy by 1. However, the institutional investor demand shock triggered a supply response: for each home institutional investors purchased, builders built 0.33 homes and small landlords sold 0.44 homes. On the other hand, institutional investors increased the number of homes available to rent by 0.56 homes for each home they purchased. In Panel B, I show that it is not 1:1 due to the crowding out of small landlords, who sell 0.44 homes. Both impacts are less than 1:1 due to supply responses. A back of the envelope calculation of the impact of institutional investors on homeownership that does not incorporate supply responses overestimates the impact by 4x.

I examine if the rentals that institutional investors supplied increased neighborhood access for the financially constrained. I plot the model output of the amount of owner-occupied homes and rentals that each income groups gains or loses when institutional investors enter in Figure 6. Households with incomes between 25–50k lose the most homes for owner-occupancy because homeowners with these incomes are most exposed to the institutional investor shock. By supplying rentals, institutional investors increased the rental supply for the lowest income renters, who are most elastic to changes in rents. The results are consistent with the descriptive analysis which showed that those who moved into institutional investor homes came from areas with lower median household incomes.

For prices, institutional investors' demand shock caused prices to increase by 2.3pp per 1pp of the total housing stock they bought. In Figure 7 Panel A, I plot the model implied impact of institutional investor entry on home purchase prices, by the share of a PUMAs housing stock that the institutional investors purchased. I also plot the binscatter of the association of these investors and actual price increases from 2012-2019 in excess of the rest of the US. 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. While the model impact is lower than the increases observed in the data, the impact is economically meaningful in the regions where institutional investors purchased the most homes. In the most concentrated PUMAs, prices increased by 10%, which on a $300,000 home is $30,000. The model implied impact is not monotonically increasing in institutional investor share because each PUMA has a different price elasticity due to heterogeneity in those who live there, as well as a different supply elasticity. For the majority of regions where institutional investors entered, almost all of the observed price association is not due to these investors. Additionally, investors only entered 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. I show the model implied impact of institutional investors on single family rents in 7 Panel B. The x axis is the share of a PUMAs single family rentals that institutional investors make up after entry. Institutional investors decreased rents by 0.8pp per 1pp of the total housing stock they bought. The model implied rent impact is in the opposite direction of the data association, suggesting that rents would have gone up in institutional investors' absence. This impact incorporates both the market power of the investors and the operating efficiency. The investors are efficient enough operators that even with market power, they increase the number of rentals and decrease rents. If policy makers consider only the market power channel, they would get the direction of institutional investor impact on rent wrong.

Institutional investor entry caused a price increase that led to capital gains for those who held homes throughout the period of this price increase. In the model, I calculate the capital gains of groups of households due to the price increase caused by institutional investors. I plot the model implied capital gains for each group in Figure 11. The highest income and middle income households get the most capital gains, due to a combination of who is most exposed to the investors and who is least likely to leave. The middle income groups are the most exposed but are also more likely to sell their homes, and high income homeowners are not as exposed but do not move at all in response to the demand shock.

I examine whether it's likely that the price and rent increases were due to institutional investors targeting regions where prices and rents would have gone up without their entry. In the ACS, I examine the change in number of households from 2012-2019 as a function of institutional investor exposure. I plot the association in Figure B2 Panel C. The areas where institutional investors purchased homes experienced outsized population gains when compared to the rest of the country. The investors in their IPO filings indicated that they targeted areas with expected population growth, to attempt to find areas with expected price and rent appreciation. The shape of the population curve matches the shape of the price and rent associations in Panel A, suggesting that institutional investors did not cause price and rent increases, but population growth caused them. The shape of the price and rent associations is not what one would expect if institutional investors caused the increases. One would expect monotonically increasing prices and rents with institutional investor presence, which is not what we see.

VI.B Economic Channels

To examine how much of the rent impact is due to market power, I simulate a merger between two of the four large landlords who enter the housing market in the model. I simulate a merger with no adjustment costs by comparing quantities and rents when 3 large landlords enter the market to when 4 enter the market. I plot the changes in rents and quantities by PUMA in Figure 8. Panel A shows that in the median area of overlap, single family rents increased by 0.71%. This effect is increasing in the share of rental housing owned by institutional investors. The size of this channel is consistent with that measured in Gurun et al. (2023), which uses quasi-experimental variation due to mergers of large landlords and finds a rent impact of 0.5% in the region of overlap. The market power here is due to these companies operating fewer rental properties. 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 median of 0.42% in the overlapped regions, and is decreasing in the market share of the institutional investors. The 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. I show this graphically in Figure 9. A merger here would move the equilibrium from 4 to 3, raising rents and decreasing quantities.

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. I show the price impact in Figure 10. The price impact would have been 2.8x as large had there been no construction response: 6.5pp per 1pp of housing stock purchased by institutional investors. This suggests that supply responses played an important role in mediating the price impact. Similar sized demand shocks to regions with less elastic supply would have caused larger price impacts.

VI.C Policy Simulations

I simulate two government policies, a large tax on investors which leads to an effective ban, and a rent increase cap for only large landlords.

Two policy proposals lead to an effective ban of large landlords from single family homes: The End Hedge Fund Control of America Act and the American Neighborhood Homes Protection Act. Both charge a tax of either $10,000 or $50,000 per home per year for each home a landlord owns above either 50 or 75 single family homes. The smaller tax, the $10,000, would more than double the operating costs of AMH and INVH, and therefore effectively ban 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 I remove the 7 large landlords I study from the homes in their exact footprint from 2019. I then observe market clearing prices, rents, and quantities. I show the impact on prices in Figure 10. Prices decrease by 10pp per 1pp of the housing stock institutional investors own, and rents increase by 1pp per 1pp of the rental housing stock in a PUMA they own. 58% of the homes vacated go to small landlords. The End Hedge Fund Control of American Homes Act requires that large landlords sell only to households, rather than households and landlords. This would lead to all of the homes going to households, however price decreases and rent increases would be even larger.

I also simulate a 5% rent growth cap for corporate landlords by taking the estimated structural model for 2012 and changing the expected rent growth for large landlords to be capped at 5%. I find that institutional investors enter the market and buy 19% fewer rentals. I show the changes in rents and quantities relative to the baseline in Figure 12. Rents are higher relative to the no rent increase cap counterfactual in regions where this cap would be binding, because large landlords decrease quantities in regions where they expect this to be binding.

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

VII Conclusion

This paper shows that the entry of institutional investors who benefit from economies of scale and market power, into the single family rental market matters for prices, rents, and homeownership. Institutional investors can scale efficiently, which leads them to accumulate large portfolios and potentially have market power. This matters for the housing market because they can supply rentals cheaper, but also have a higher willingness to pay for housing which can raise prices. The large portfolios also give them market power. I estimate the impact of institutional investors on the housing market by building a structural model that incorporates landlord type heterogeneity.

I find that institutional investors did not cause the majority of the price increases that occurred where they bought homes. A large construction response and the crowding out of small landlords are of first order importance in mitigating the effect of their demand shock on prices and homeownership. I find that market power is not the driving mechanism of investor impact in the rental market, and is outweighed by the operating efficiency of large landlords which on net decreases rents. This estimation shows that concerns about homeownership impacts must consider supply responses, and that concerns about market power must be weighed against the fact that institutional investors increase the number of rentals due to their operating efficiency and on net decrease rents. Landlord operating cost differences matter for the housing market and drive the net effect in the rental market, highlighting that landlord differences are of first order importance to the housing market.

The associations of institutional investor entry with increases in prices and rents appear to be driven by selection: the investors targeted neighborhoods with expected population growth, and the areas they entered ended up experiencing large population increases relative to the rest of the country. Overall, I show that the popular narrative that institutional investors are raising prices is overstated, and that the concern that they increase rents through market power is directionally incorrect. The upward pressure of market power on rents is relatively small when compared to how much institutional investors increase the rental supply by entering the market. Therefore policies that decrease institutional investor supply, like a ban and rent increase limits, are counterproductive and cause rent increases. Additionally, large landlords are now starting to build more homes to rent them out. Because this paper provides a flexible framework through which one can study many housing market topics that include landlord type heterogeneity, construction, and household behavior, future work can study the incentives of landlords to build homes and how that can impact the housing market.

References

Almagro, Milena and Tomas Dominguez-Iino, 'Location Sorting and Endogenous Amenities: Evidence from Amsterdam," Working paper 2024.

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.

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.

Billings, Stephen B. and Adam Soliman, 'The Erosion of Homeownership and Minority Wealth," Working paper 2023.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 'Why is Intermediating Houses so Difficult? Evidence from iBuyers," Working Paper 2022.

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.

Chodorow-Reich, Gabriel, Adam M Guren, and Timothy J McQuade, 'The 2000s Housing Cycle with 2020 Hindsight: A Neo-Kindlebergerian View," *The Review of Economic Studies*, 04 2023, p. rdad045.

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.

Demers, Andrew and Andrea L. Eisfeldt, 'Total returns to single-family rentals," *Real Estate Economics*, 2022, *50* (1), 7–32.

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.

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 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?," Review of Financial Studies 2023.

Jiang, Zhengyang, Robert Richmond, and Tony Zhang, 'A Portfolio Approach to Global Imbalances," *Forthcoming, The Journal of Finance*, 2023.

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.

_, Robert Richmond, and Motohiro Yogo, 'Which Investors Matter for Equity Valuations and Expected Returns?," *Forthcoming, Review of Economic Studies*, 2023.

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.

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

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.

Raymond, Lindsey, 'The Market Effects of Algorithms," Working Paper 2024.

Saiz, Albert, 'The Geographic Determinants of Housing Supply," *The Quarterly Journal of Economics*, 2010, *125* (3), 1253–1296.

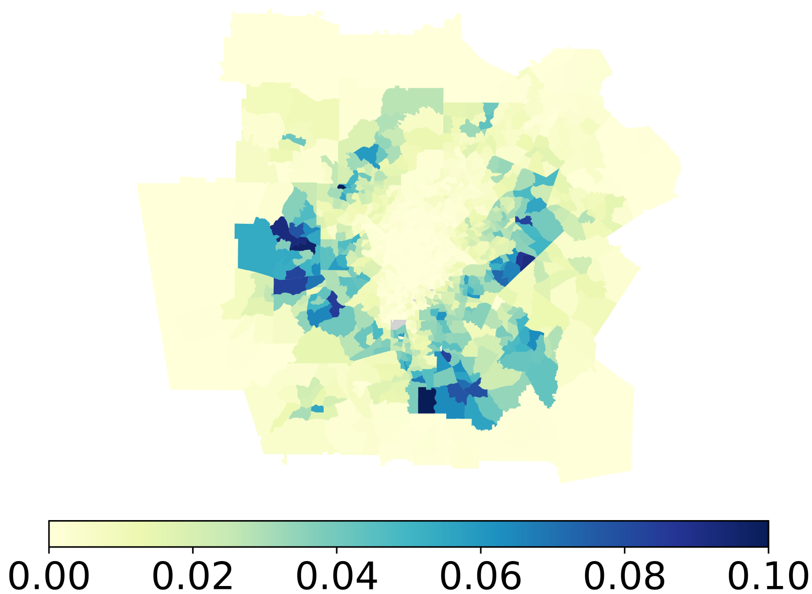
Schubert, Gregor, 'House Price Contagion and U.S. City Migration Networks," Working paper 2021.

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

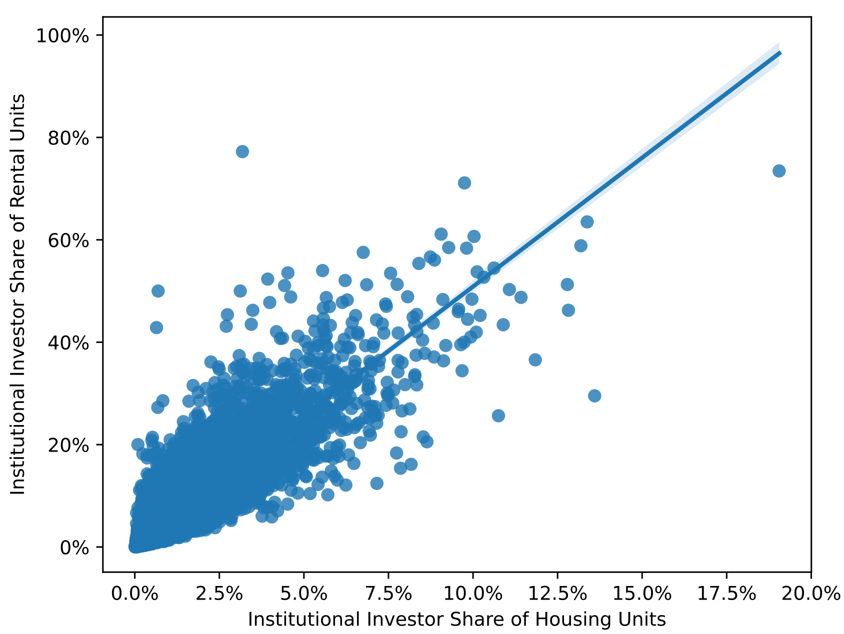
VIII TABLES AND FIGURES

Figure 1: Tract Concentration of Institutional Investors (2021)

Panel A: Fraction of Housing Units Owned in Atlanta



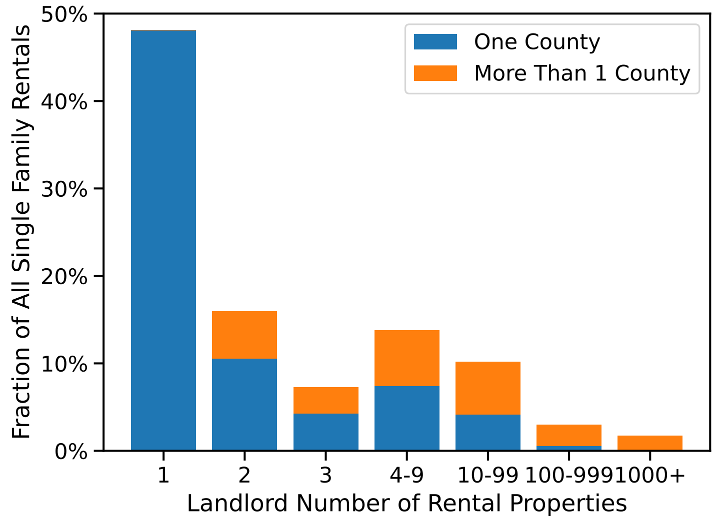
Panel B: Fraction of Rentals Owned vs Housing Units in the US



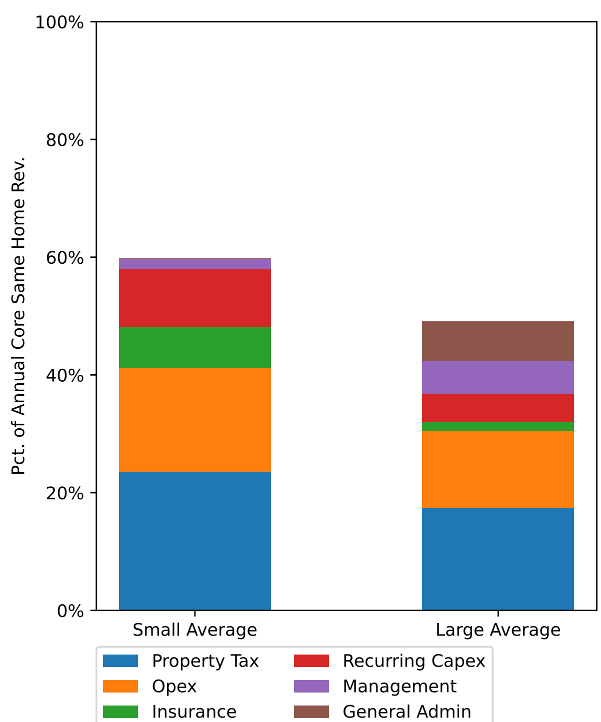
Notes: Panel A shows the fraction of residential housing stock in a census tract owned by the 7 largest institutional investors in February of 2021 in the counties including and surrounding Atlanta, GA. The investors included are Invitation Homes, American Homes for Rent, Tricon Residential, FirstKey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

Figure 2: Scale comparison between small and large landlords

Panel A: Distribution of Single Family Rentals By Operator Size



Panel B: Difference between large and small landlord operating costs

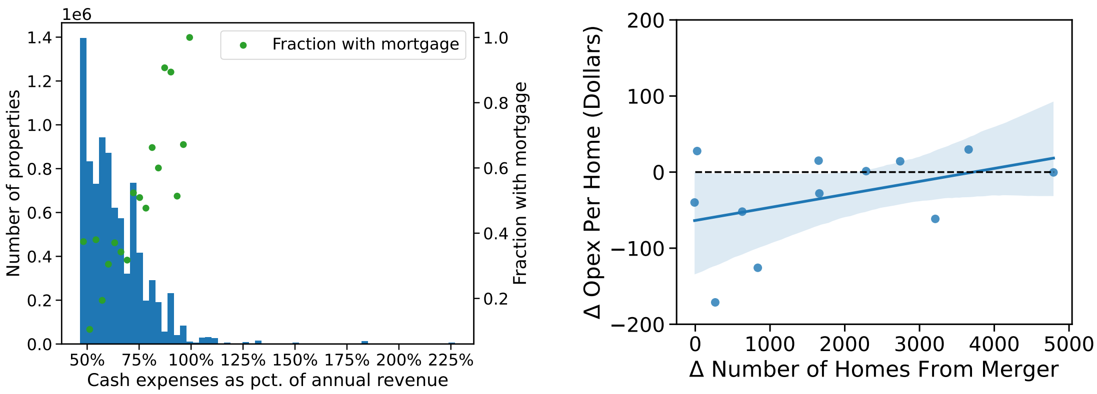


Notes: Panel A shows the fraction of all single family rentals in the US that each operator size bucket owns, and within each operator size bucket, the fraction that operates in only one county or multiple counties. Data come from a Verisk property snapshot from February 2021. Rental status is determined by whether the mailing address is the same as the property address. Panel B shows operating costs for the average 1 unit individual landlord in the Rental Housing Finance Survey, compared to operating costs for the average of Invitation Homes and American Homes for Rent, where data come from their earnings statements supplements. Data are from an average of fiscal year 2017 and 2020. For Invitation Homes and American Homes for Rent, all data except for General Admin, Management, and Insurance are from their "same home portfolios", which excludes recently acquired homes or homes that are preparing 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 between small and large landlords

Panel B: Cost Heterogeneity for Small Landlords

Panel A: Change in Opex Per Home From INVH and SWH Merger

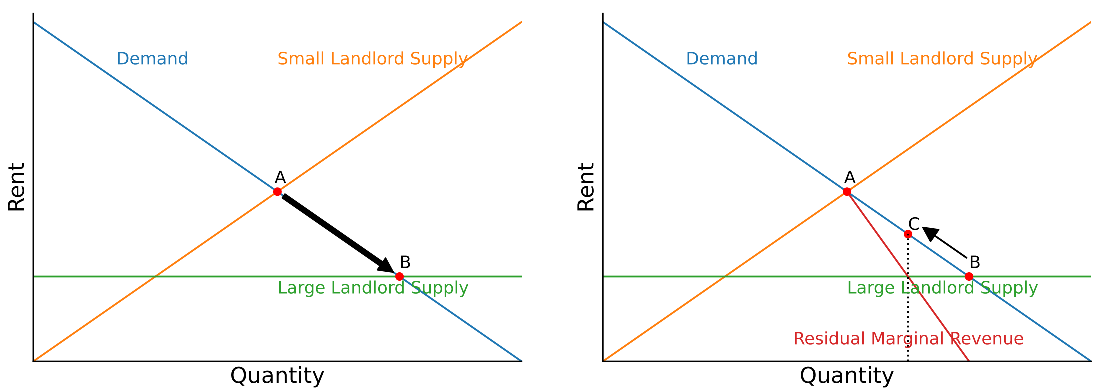


Notes: Panel A shows a histogram of individual 1 unit landlords in the Rental Housing Finance Survey. The entries are distributed by cash expenses as a fraction of rent revenues. The green dots are the fraction of operators in each bucket who have a mortgage. Panel B shows for Invitation Homes, the change 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: Stylized Example of Large Landlord Entry

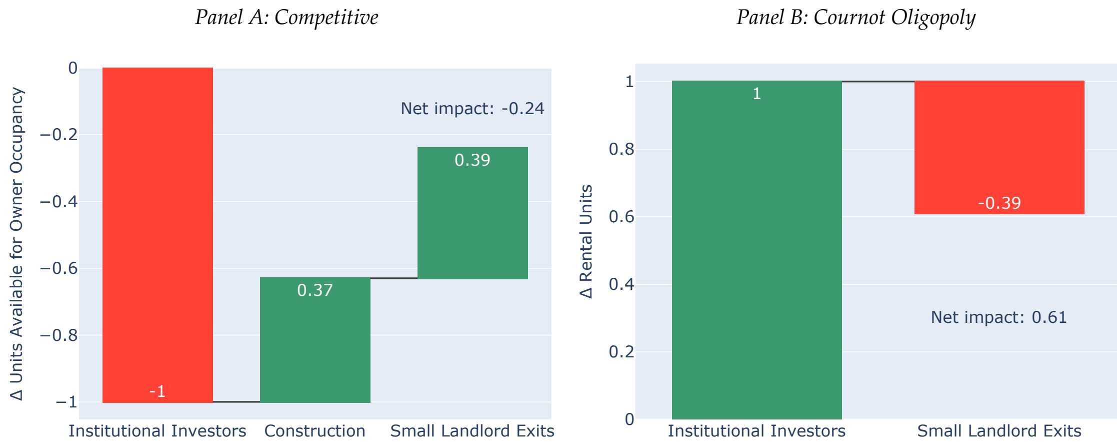
Panel A: Competitive

Panel B: Cournot Oligopoly



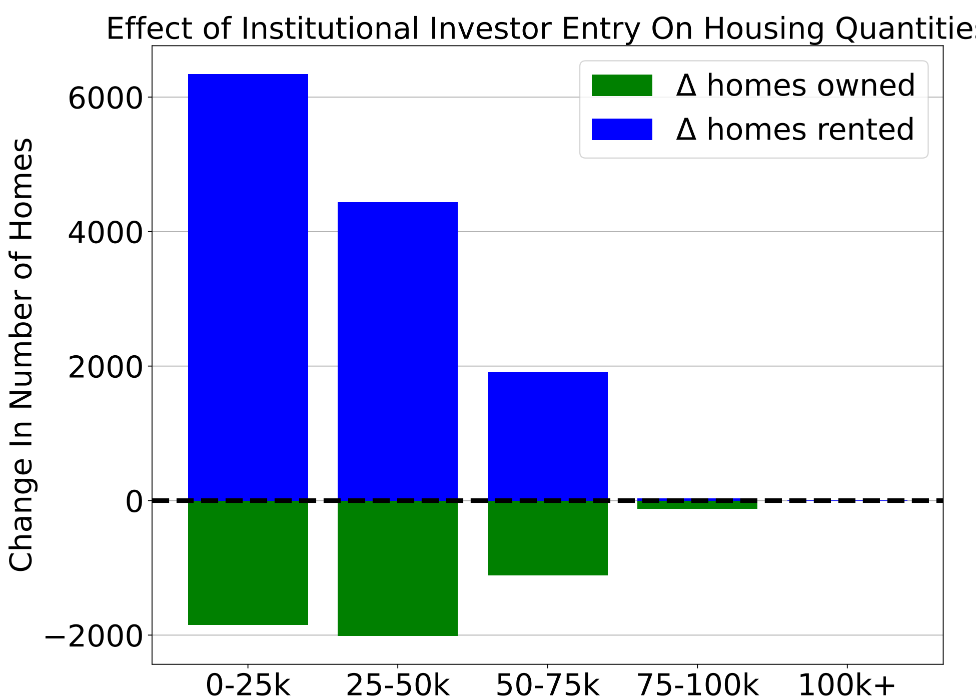
Notes: This figure shows a stylized model of supply and demand for single family rentals. Households have upward sloping demand and small landlords have downward sloping demand. In Panel A, one large landlord with constant returns to scale enters and behaves competitively, shifting the equilibrium from A to B. In Panel B, the large landlord chooses a quantity where residual marginal revenue intersects its cost curve, shifting the equilibrium from B to C.

Figure 5: Quantity changes when institutional investors enter



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.

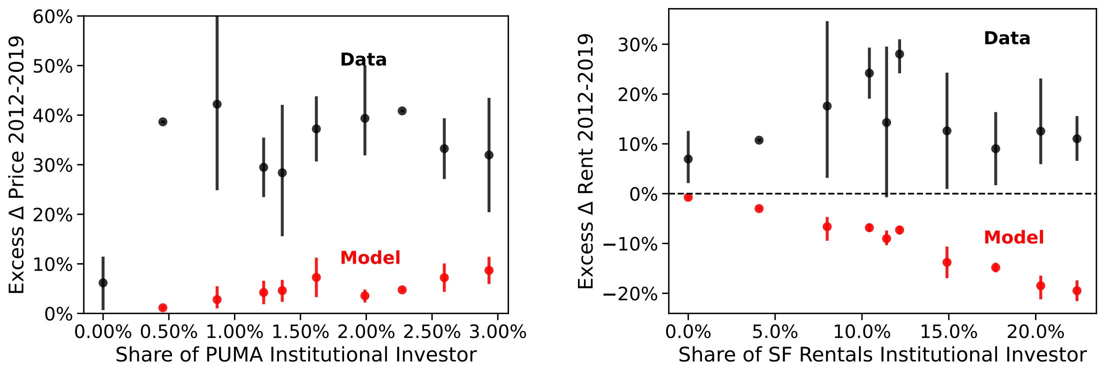
Figure 6: How do groups lose homes / gain rentals when institutional investors enter?



Notes: In the simulation where institutional investors enter the housing market, this figures show how each groups' housing allocations change. The blue bars shows the number of rentals a group gains. The blue bars show the number of owner occupied homes a group loses. They do not sum to the same number because a group can move from the modeled outside asset, which consists of PUMAs with no 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, or the unmodeled outside asset which would be equivalent to positive or negative household formation.

Figure 7: Price and rent changes when institutional investors enter

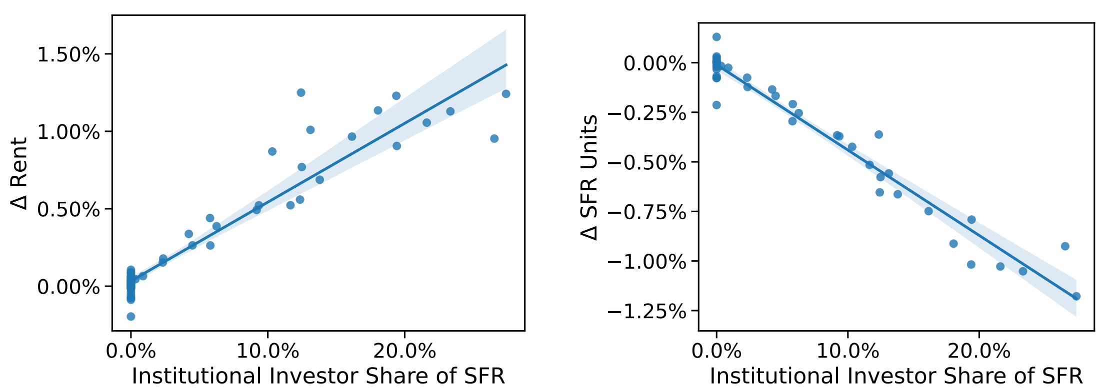
Panel A: Competitive *Panel B: Cournot Oligopoly*



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 PUMAs housing stock or rental stock they own, and they y axis shows the excess increase in price or rent compared to the rest of the US. The black binscatter shows the data association from 2012-2019 of these investors with prices and rents. The red binscatter is the model output.

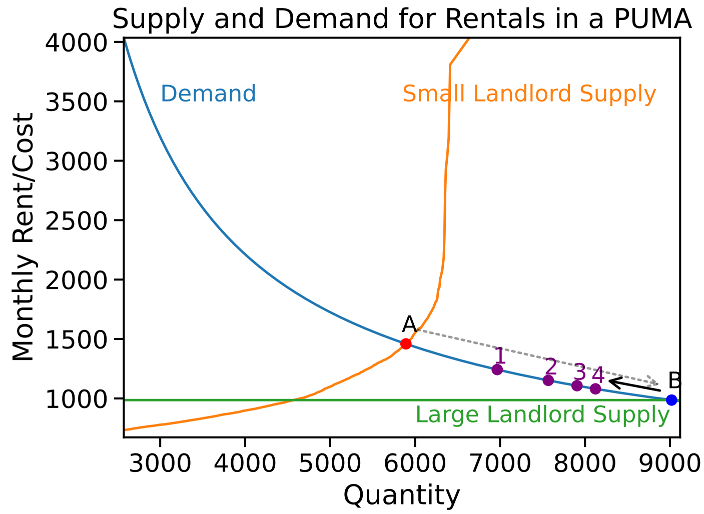
Figure 8: Impact of a large landlord merger

Panel A: Change in Rents *Panel B: Change in Quantities*



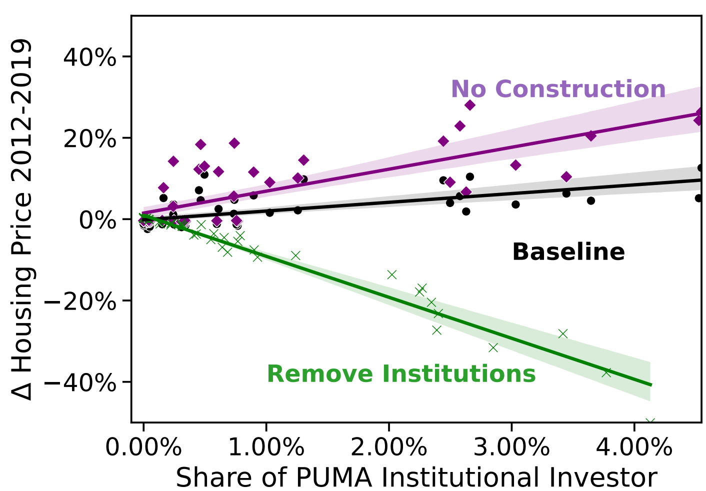
Notes: This figure shows the model implied impact of two large landlords merging, with no adjustment costs. Panel A shows the change in single family rents due to the merger in each PUMA, and Panel B shows the change in the quantity of single family rentals in each PUMA. The X axis is the institutional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

Figure 9: Stylized example of merger



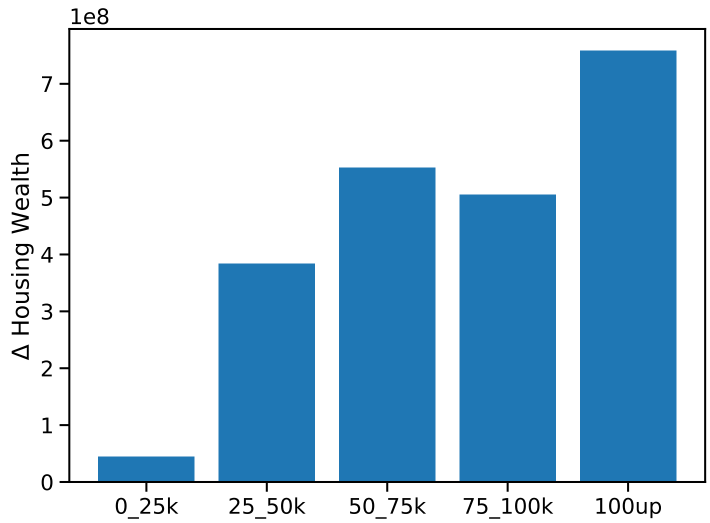
Notes: This figure shows the equilibrium quantities and rents for one PUMAs single family rental market when there are no large landlords (A), when there are either infinite or the ones that exist choose competitive quantities (B), and then when there are 4, 3, 2, or 1 large landlords. A merger between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

Figure 10: Price impact in counterfactual experiments



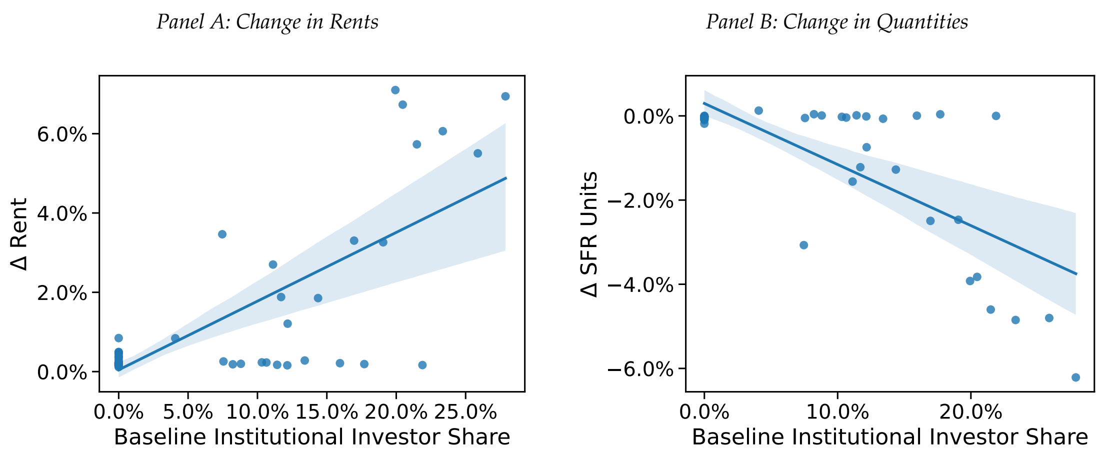
Notes: This figure shows the price impact in each PUMA for the baseline estimation and various counterfactual experiments.

Figure 11: Institutional Investor Impact on Housing Wealth



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

Figure 12: Impact of a 5% Rent Increase Limit on Large Landlords



Notes: This figure shows the model implied impact of a 5% rent increase limit on large landlords. Panel A shows the change in single family rents and Panel B shows 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 rent increase limit.

Table 1: Difference in Tract Characteristics For Movers Into Institutional Investor 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 between destination tract characteristics and origin 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 ACS, the second row is the difference in 2013 math test scores from Opportunity insights, the third row is teh difference in historical likelihood to go to jail from Opportunity insights, and the final row is the historical likelihood to get into 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 tract data. Clustering is at the new tract level. It compares within a given new tract, those who move into an institutional investor home for the first time vs 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 ACS 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 end up in jail and the fraction who end up in the top income quintile. These represent historic mobility measures, not future outcomes. The outcome variables in columns 3-5 come from Opportunity Insights.

APPENDIX

A DATA APPENDIX

A.1 Property Sample

Steps to construct the Verisk property sample:

- Keep properties that have a property indicator for single family residence, townhouse, apartment, condominium, duplex, triplex, or quadplex
- Exclude properties with no street information
- Exclude mobile homes
- Exclude remaining properties with a duplicate address indicator
- owner-occupied: owner-occupied flag of O or S. A, T, and null I call rentals.

Table A1: Verisk Housing Units By Zipcode Compared to Census Units

	Total Units	Owner Occupied	Rental Units
Units	1.064***		
	(0.001)		
Owner Occupied Units		0.991***	
		(0.001)	
Units Not Owner Occupied			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 regresses 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, the third is rental.

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. Also, for multi-unit apartment buildings, sometimes Verisk has one row for each apartment in the building and other times it has one row for the entire apartment where the apartment number field details the number of apartments in that row. However, sometimes there are rows that look like they should represent one apartment but have the entire building's number of units as the apartment number. To clean 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. If that's the case, I change the number of units for that row to be 1. I also change to 1 the apartment number of any row that has a living sqft per unit of less than 100.

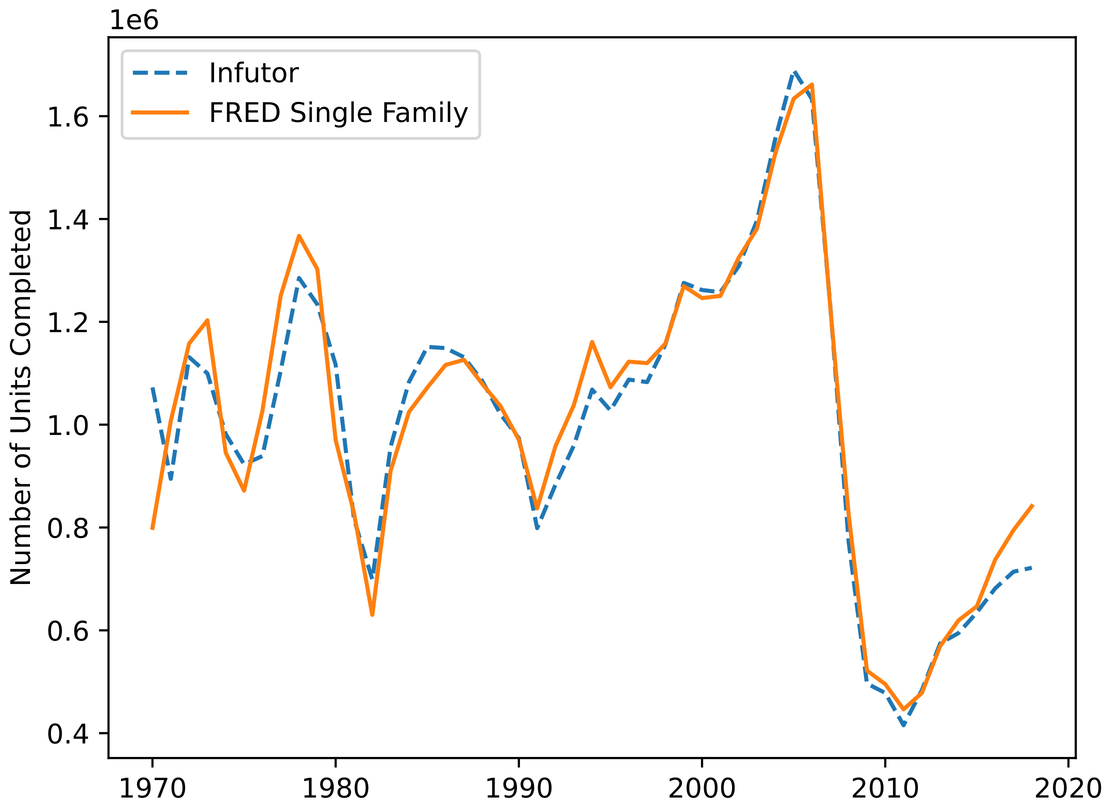
I validate the number of institutional investor owned homes I am able to identify for each public company in the table below. The identification is described in the data section of the paper.

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 takes the number of units belonging to each company identified with Verisk data and compares it with information available in SEC filings for 2020Q4.

Figure A1: Supply validation



Note: I plot the aggregate number of completions for the US each year from Verisk, where I infer the year a property was built to be its completion date. I compare this with aggregate US completions for single family homes data from FRED.

A.2 Mover Sample

Steps to construct the Verisk moving sample:

- Clean property dataframe for 2019 as described above
- Take the Verisk moving history and exclude anyone who has a deceased flag of Y or null

I use an anonymized dataset so I can't 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.

- Reshape from wide to long to get the dataset at the person ID x address x previous address level, with the date recorded at the previous address and date recorded at the current address
- I drop those with null zipcodes, true duplicates, and duplicates

At this stage, there are many duplicate PID x EFFDATEs. I want to identify one address at a given date for a given person.

- Of the duplicates at the PID x EFFDATE level, I drop those that don't 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. I keep the duplicate that has the first rank in that order.
- I drop all entries that have remaining duplicates, and do not select one of the duplicates to keep

From this 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 2012-2019. 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, where 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.

- Create moving window for 201811-201911
- Clean property dataframe for 2018
- For each property, the 2018 owner is the old owner and the 2019 owner is the new owner
- Merge the moving window dataframe to the 2019 property frame
- Use 2019 property frame for the attributes of where people moved from and where they moved to

- Merge to cleaned 2019 demographic file
- Create flags for indicator variables
- Output those who have moved

Table A3: Mover level Validation Moves To and Moves From

	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 regresses Verisk moves on USPS zipcode moves. The first column compares moves out of a zipcode in both datasets. The second column compares moves into a zipcode in both datasets.

Table A4: Mover level County To County Validation

	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 regresses Verisk county to county moves on Census county to county moves.

A.3 Small Landlord Costs

To construct a dataset of small landlord single family rental cost components, I start with the 2018 and 2021 Rental Housing Finance Survey's publicly available data. I filter the dataset as follows:

- Keep only 1 unit properties

- Keep only ”individual” type owners, which excludes corporations, REITs, and LLCs
- For 2021, I am able to exclude townhouses but for 2018 this field doees not exist
- I exclude assisted living homes and rent control homes
- I keep homes only with lease lengths of 1 year
- I keep homes with rent and market value both greater than 0

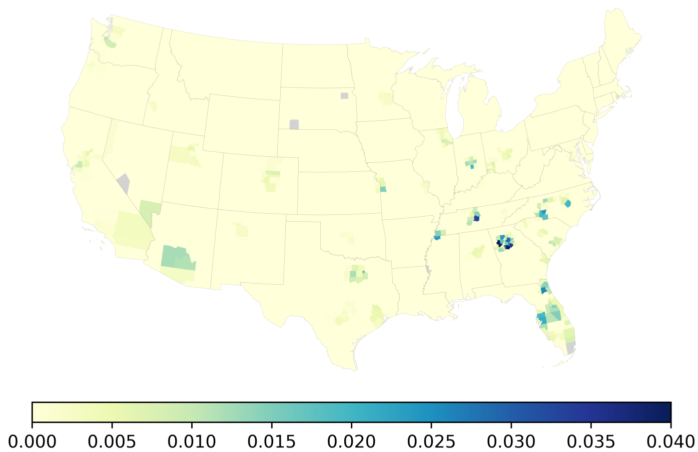
This results in a dataset of 601 individual landlords of 1 unit properties.

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 is bucketed. Buckets are the same for both the 2018 and 2021 samples. I choose the mid point of each bucket to be the dollar amount of property taxes paid for the descriptive analysis. Some landlords in the RHFS report having a mortgage in the field where they say they have a mortgage 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 B7, small landlords appear to pay off their mortgages over time and appear to mostly have 30 year mortgages. For the descriptive analysis, I want their interest expenses each year as a fraction of rent, assuming this mortgage payoff activity. I take the present value of the expected interest payments if these landlords pay off 1/30th of their mortgage each year, and then turn this into a perpetuity equivalent to get 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. My goal would be to 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 across landlords that are likely to be highly variable from year to year: recurring capex, repairs, and electricity and gas. I windsorize 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 get 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: handicap access, 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.

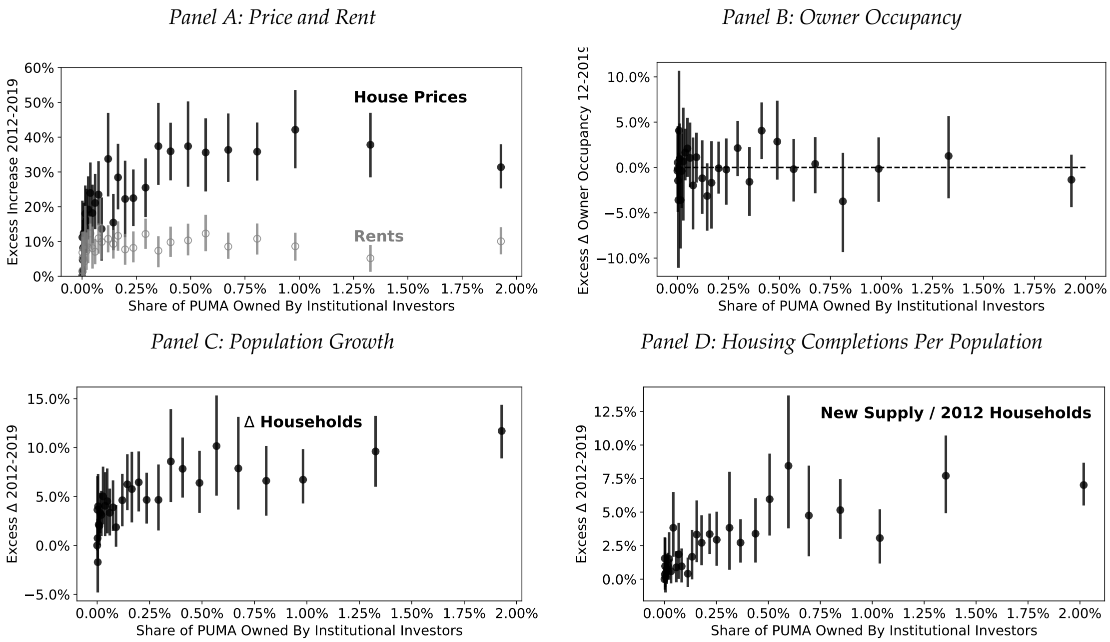
B Additional Figures and Tables

Figure B1: Fraction of Housing Owned by Institutional Investors in February 2021



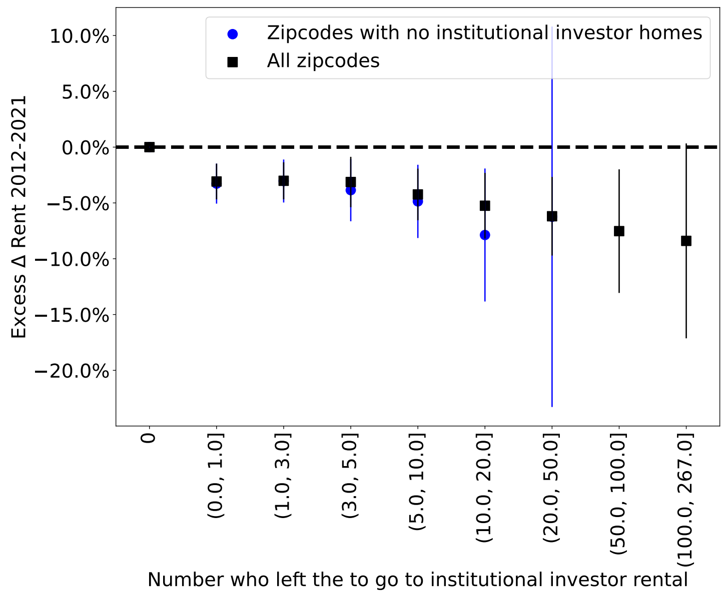
Note: For the US in February 2021, I show the fraction of the total housing stock that 7 institutional investors combined own at the county level. The 7 I include are Invitation Homes, American Homes for Rent, Tricon Residential (now owned by Blackstone), Progress Residential, FirstKey Homes, Main Street Renewal, and Home Partners of America.

Figure B2: Associations with Institutional Investor Share of Housing Stock



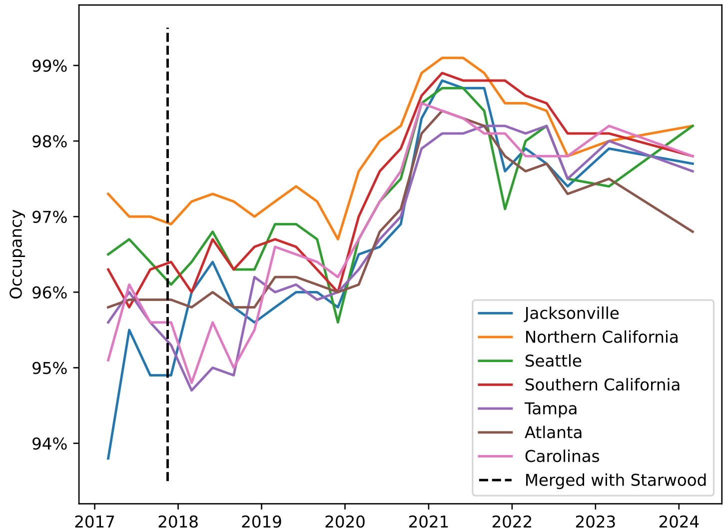
Notes: This figure shows the coefficients of a regression of different PUMA level variables on the fraction of the housing stock owned by institutional investors. PUMAs with no institutional investor presence are the intercept, so each plot shows the excess of the variable relative to the rest of the country. Panel A is the change in the fraction of homes owner-occupied from 2012–2019 from the ACS1. Fraction owner-occupied for a given age group is the number of owner-occupied households in the age group divided by the number of all households. Panel B is the change in fraction owner occupied from 2012–2019 from the ACS1. Panel C is the change in the number of households from 2012–2019. Panel D is the amount of new construction from 2012–2019 divided by the number of households present in 2012. The new construction counts come from the Verisk property files.

Figure B3: Association of out-migration to institutional investor rentals and rent changes



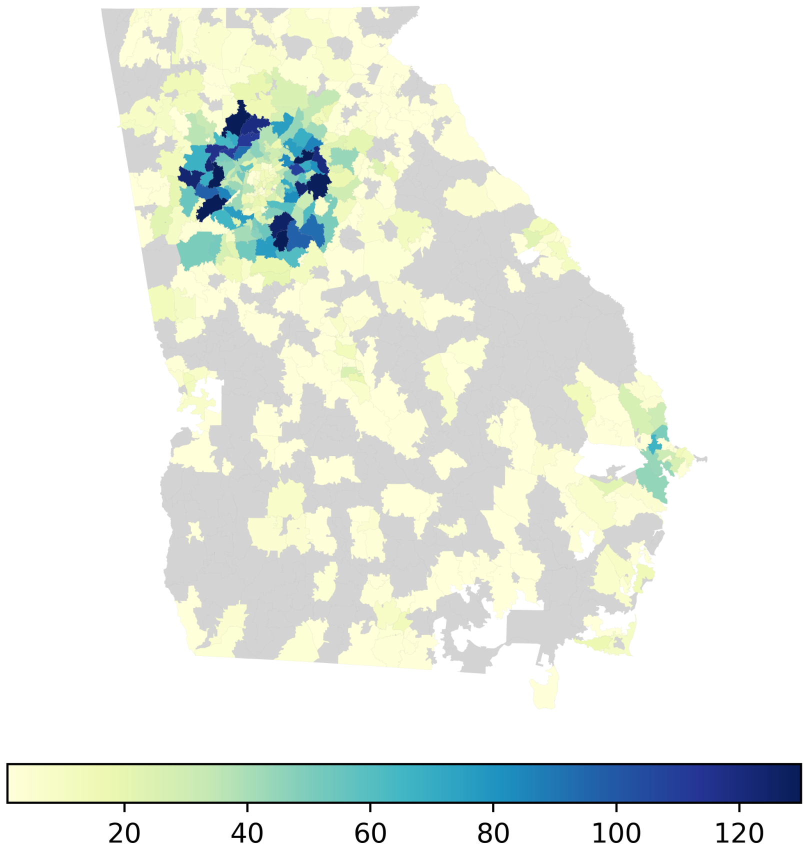
Note: This figure plots the coefficients of a regression of the percentage change in zipcode rent as a function of the number of people who left that zipcode to move into an institutional investor home. The regression is run twice, first including all zipcodes where someone left to go to an institutional investor home and second for zipcodes that contain no institutional investor homes themselves. Zipcode level rents come from the American Community Survey 5 year tables and are the difference between 2021 rents and 2012 rents. The number of people leaving a zipcode to move into an institutional investor rental come from Verisk.

Figure B4: Market level occupancy rates for Invitation Homes



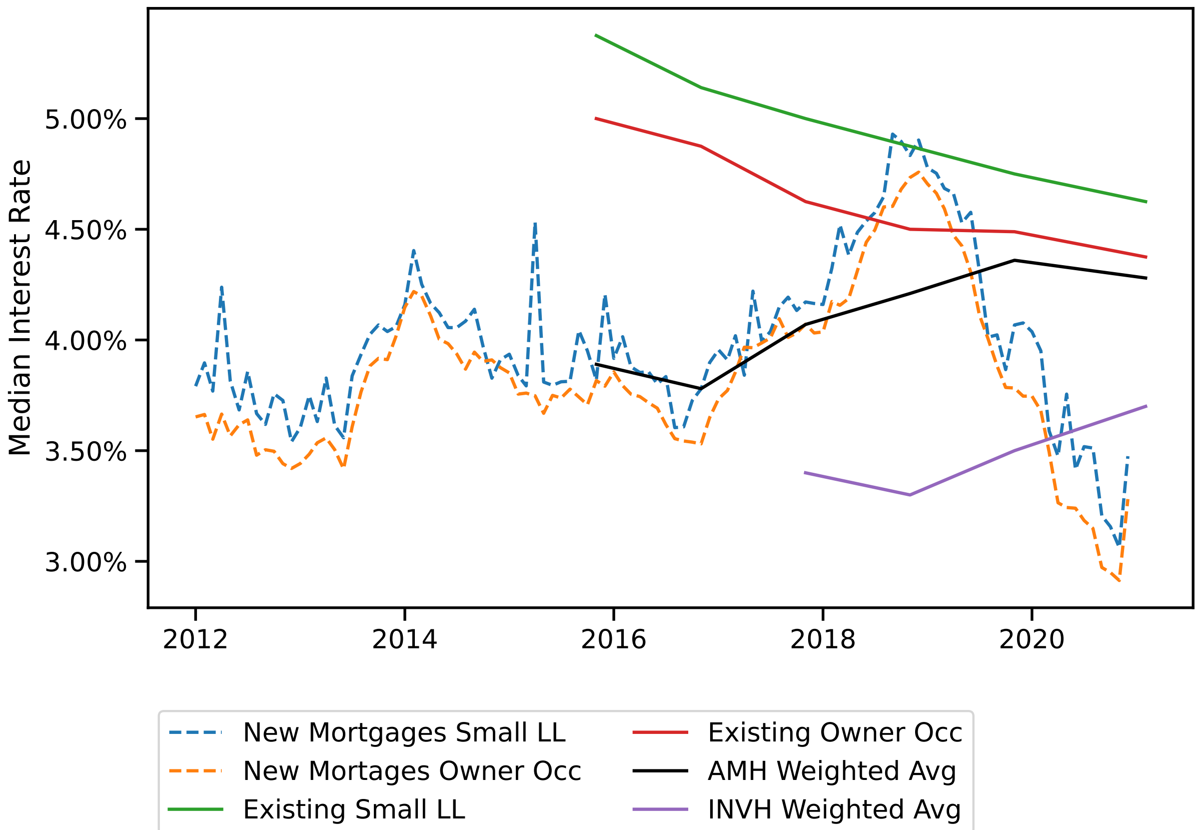
Note: This figure shows the market level occupancy for Invitation Homes for a number of its markets. The dotted black line is the date where Invitation Homes merged with Starwood Waypoint Homes and gained 32,000 homes.

Figure B5: Where did those who rent from institutional investors come from?



Note: This figure shows the origin locations of those who moved into an institutional investor home between Jan 2012 and Feb 2021. For each home, I include the movers only after the most recent sale date of the institutional investor home. I exclude those who moved from one institutional investor home to another institutional investor home.

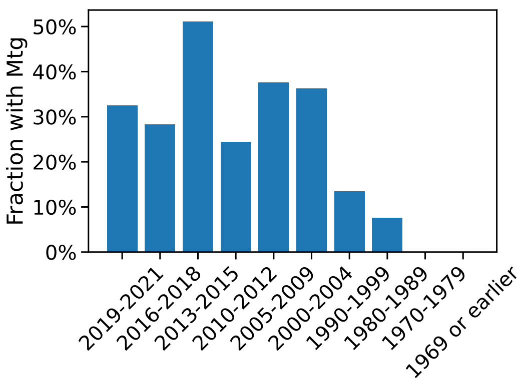
Figure B6: Cost of Debt



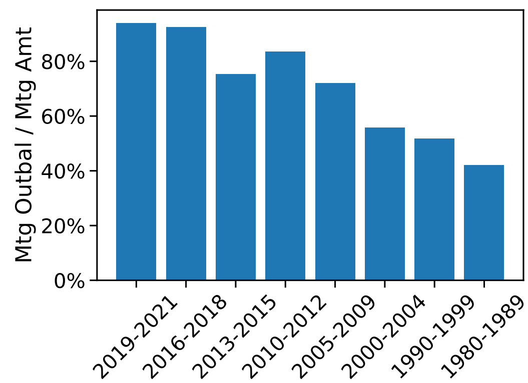
Note: This figure shows median interest rates for new mortgages for small landlords, new mortgages for owner occupied homes, all existing mortgages for small landlords, all existing mortgages for owner occupants, American Homes for Rent's debt, and Invitation Homes' debt. Data for the small landlords 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 timeseries is limited to after its IPO date.

Figure B7: Small Landlord Mortgages

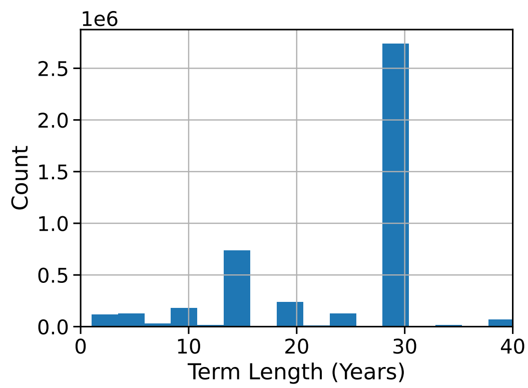
Panel A: Fraction of Small Landlords with Mortgage by Purchase Date



Panel B: Mortgage % Remaining

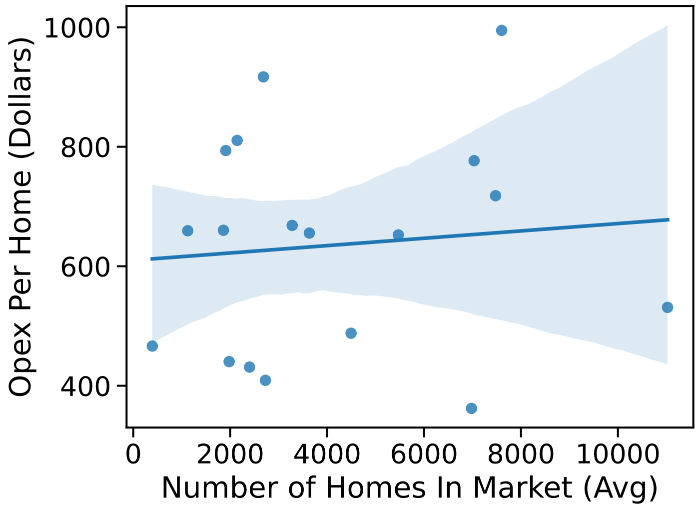


Panel C: Small Landlord Term Length Distribution



Notes: Panel A shows the fraction of a small landlord bucket that has a mortgage in the 2021 vintage of the RHFS, where each bucket is a purchase date grouping. Panel B shows the fraction of the original mortgage balance remaining for each purchase year bucket for those who still have mortgages. Panel C shows the distribution of small landlord term lengths from the Verisk data. 2/3rds of the small landlords with mortgages in the Verisk data have data for term lengths. I show the distribution from the data cross section in November 2015.

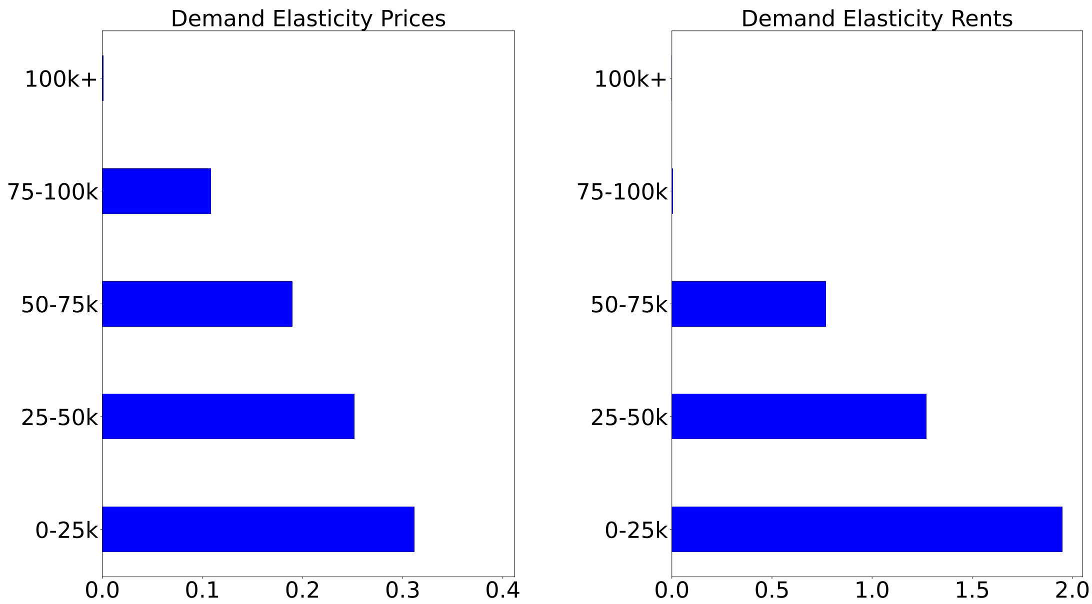
Figure B8: INVH Market Average Opex Per Home



Note: This figure shows Invitation Homes' market level average operating expenditures per home, by the number of homes in each market.

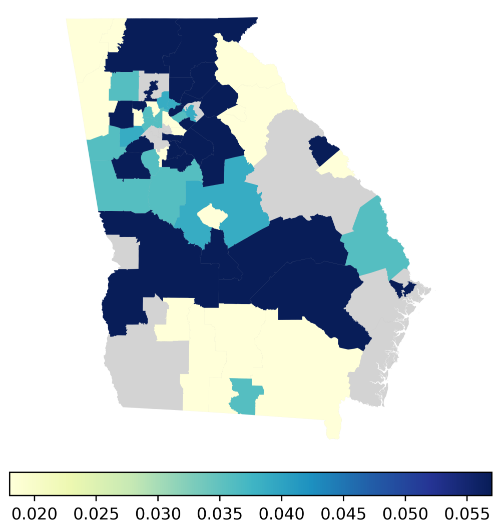
Figure B9: Demand Elasticities

Panel A: Owners *Panel B: Renters*



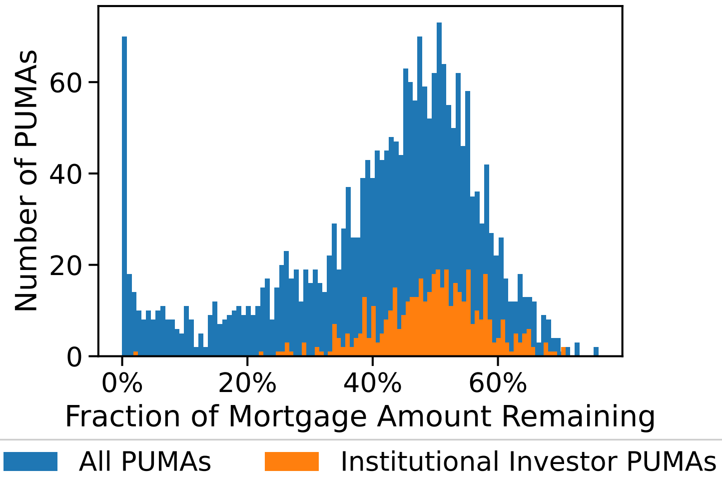
Notes: This figure shows the PUMA level moving elasticities to prices and rents of aggregate groups of households as estimated by the demand system. Elasticities are estimated using ACS1 data from 2012–2019 at the PUMA x year level. The elasticity is the percentage that each group decreases its quantity when price or rent increases.

Figure B10: Expected rent growth



Note: This figure shows the expected rent growth from 2012 forward for both landlord types. 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 be the expected 5 year rent growth nationally from 2014 from the NY Fed's SCE data. 2014 is the earliest year of publicly available SCE data.

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 average small landlord mortgage balance outstanding as a fraction of sale price. The blue histogram shows all PUMAs, and the orange shows the PUMAs where the 7 institutional investors studied in this paper own at least 100 units combined as of November 2019. 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 2012 or earlier are used here.

Table B1: Small landlord estimation

	Georgia	High Investor Activity
Corr($Q_{est,PUMA}$,$Q_{actual,PUMA}$)	97%	99%
Median $Q_{est,PUMA}$ / $Q_{actual,PUMA}$	0.82	0.91
Median Elasticity with Respect to Rent	0.51	0.35
Median Elasticity with Respect to Price	-0.58	-0.46

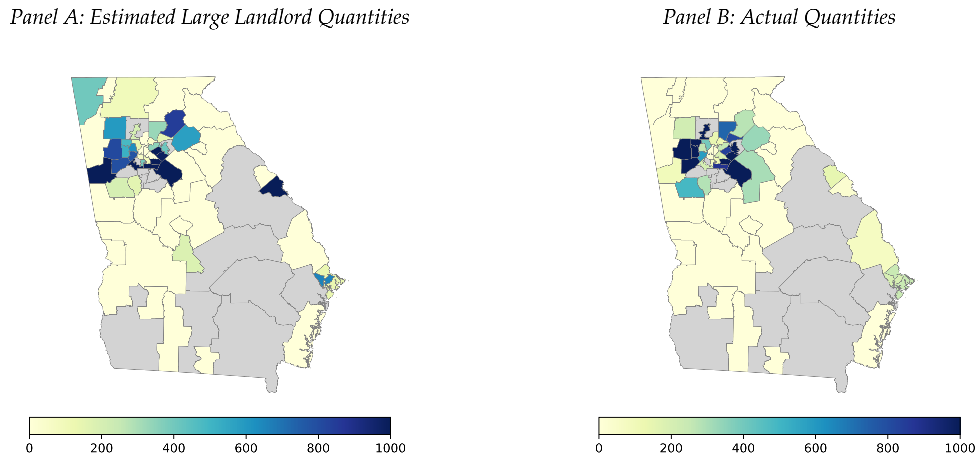
Note: This table shows estimation results when I plug in 2012 rents and prices into the small landlord estimation. I compare estimated PUMA quantities to actual quantities in 2012, for all of Georgia and for PUMAs where institutional investors have 1000 or more units which I call "High Investor Activity" 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. Then I raise rents by 1% and measure the change in quantity in each region and report the median change as the median elasticity to rent. I then raise prices by 1% and measure the change in quantity in each region and report the median as the median elasticity with respect to price.

Table B2: Small landlord fitted elasticities

	Dependent variable: Elasticity with respect to price
	Georgia
	(1)
Intercept	14.15***
	(2.59)
Expected Rent Growth Pct	0.33***
	(0.08)
Log(Price/Rent)	-2.83***
	(0.47)
Mean Mortgage Balance Pct	-2.00**
	(0.87)
Property Tax Rate Pct	-0.14
	(0.49)
Observations	57
R^2	0.55

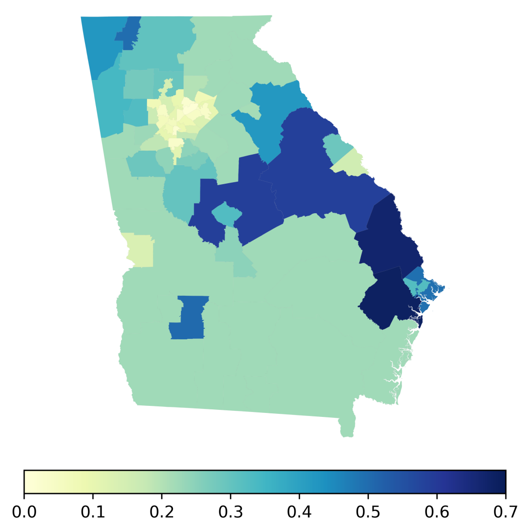
Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the regression of fitted small landlord elasticities on components of their objective function in Georgia. The dependent variable is the percentage change in small landlord quantity when prices increase by 1%. Expected rent growth pct is g_j, log(Price/Rent) 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 B12: Large Landlord Estimation Fit



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

Figure B13: Supply elasticities for Georgia



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

Table B3: Where are institutional investors located?

	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 is a descriptive regression at the PUMA level. The dependent variable is an indicator variable for a PUMA if institutional investors have 10 or more properties in that PUMA, combined. Column (1) has no fixed effects and Column (2) has state level fixed effects. Prices and rents are median values from the Census ACS 1 year tables for 2012. MF is multifamily, SF is single family. 2006 prices and population counts are from the 2006 Census ACS 1 at the PUMA level. I use a crosswalk from 2000 PUMAs to 2010 PUMAs from the Missouri Census Data Center so I can compare values from 2006 to 2012. Average annual job growth from 2004-2013 and middle school math scores from 2013 come from Opportunity Insights at the tract level, which I aggregate up to the PUMA level. Foreclosures per 2012 population comes from foreclosure data from ZTRAX from Zillow, and population data from the 2012 census. A PUMAs distance to nearest MSA comes from the distance of each zipcode in a PUMA to the center of the nearest MSA, which I then aggregate to get an 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 a PUMA that is single family. Weather controls are the January temperature and sunlight, and the July temperature and humidity. Other amenity controls come from the Census ACS 2012 1 year tables and are the fraction of high school age population that is enrolled in high school, the fraction of high school age population that is enrolled in private school, and the fraction of total population that has a commute under 45 minutes long.

Table B4: Within Zipcode 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 zipcode with the features of the rest of the rental stock and of owner-occupied homes. I take these within zipcode differences and compute a weighted average, weighted by the number of units institutional investors have in a given zipcode. This results in a weighted average within zipcode difference in physical characteristics between institutional investor homes and other types of homes.

Table B5: Migration Share IV

	$log(w_{(i,l)\to(j,k)}/w_{(i,l)\to 0})$
$sqrt(Distance_{i\to j})$	-0.0003***
$log(SCI_{i\to j})$	0.4282***
$ooc \to ooc$, same puma	-0.7401***
$ooc \to ooc$, diff puma	-7.7562***
$ooc \to sf$, same puma	-4.8917***
$ooc \to mf$, same puma	-8.0212***
$ooc \to sf$, diff puma	-8.2135***
$ooc \to mf$, diff puma	-8.8547***
$sf \to ooc$, same puma	-2.5084***
$sf \to ooc$, diff puma	-6.3004***
$sf \to sf$, same puma	-1.1680***
$sf \to mf$, same puma	-6.8053***
$sf \to sf$, diff puma	-6.6063***
$sf \to mf$, diff puma	-7.2718***
$mf \to ooc$, same puma	-2.4026***
$mf \to ooc$, diff puma	-4.3677***
$mf \to sf$, same puma	-3.3508***
$mf \to mf$, same puma	-0.0216
$mf \to sf$, diff puma	-4.6631***
$mf \to mf$, diff puma	-5.3584***
$log(Rent)$	-0.3049***
$log(Price)$	-0.1279***
Topography controls	Y
Weather controls	Y
Housing characteristics controls	Y
Amenity controls	Y
n. obs.	3304840

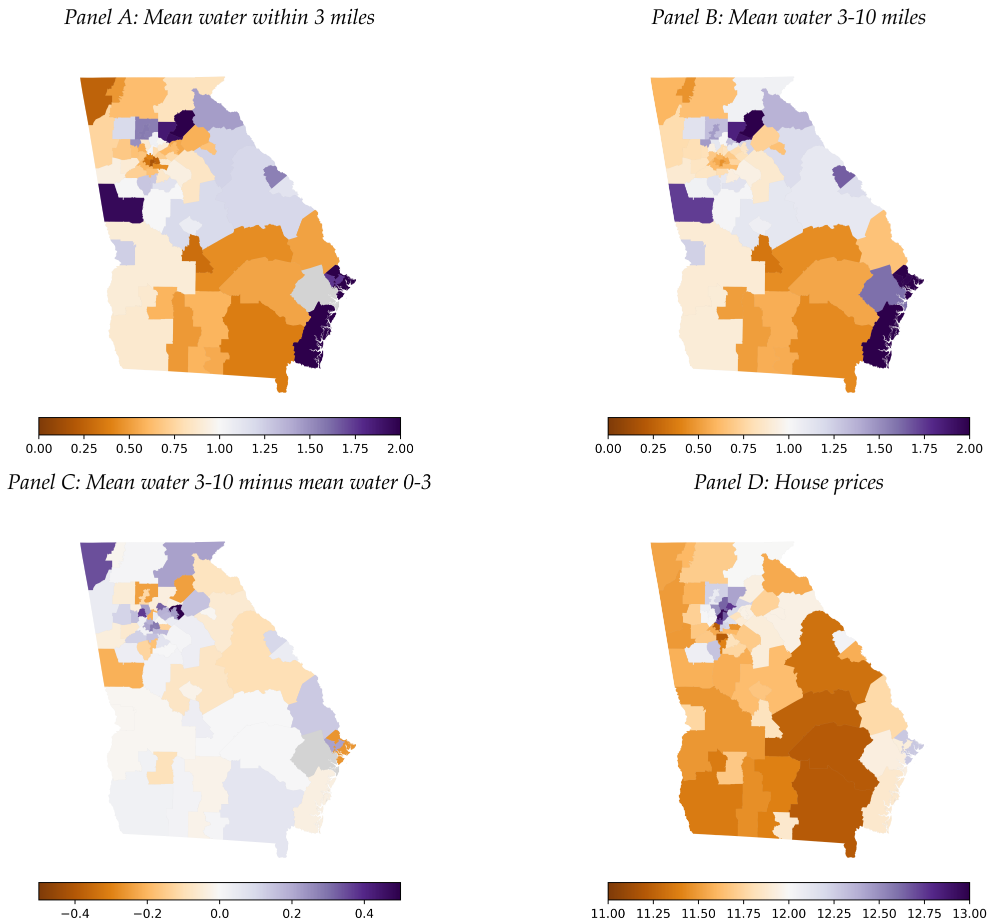
Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the IV regression of the log share of a PUMA moving from origin i to destination j divided by the share moving to the outside asset. The outside asset is defined as all PUMAs missing a non-price characteristic, or with housing prices below 80k or rent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

Table B6: First Stage For Household Demand

	log(Price)	log(Rent)
log(Land Unavail 0-3mi)	0.0028	-0.0166***
log(Land Unavail 3-10mi)	0.0647***	0.0169***
log(Wetlands 0-3mi)	0.0020	-0.0089
log(Wetlands 3-10mi)	-0.0130	0.0399***
log(Water 0-3mi)	-0.0480***	-0.0520***
log(Water 3-10mi)	0.0811***	0.0811***
med. year built	0.0003**	0.0003***
med. year built neighboring pumas	0.0001**	0.0001***
med. num rooms	-0.2672***	-0.1134***
med. num rooms neighboring pumas	-0.3221***	-0.1898***
frac. SF census	0.5803***	0.2108***
frac. SF census neighboring pumas	-0.2106***	0.1903***
Weather controls	Y	Y
School controls	Y	Y
Amenity controls	Y	Y
Year FEs	Y	Y
Partial F-stat	1000.2	1630.6
n. obs	47033	47033

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

Figure B14: Examining The Instrument



Notes: 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 but between 3-10 miles away. Panel C shows the average difference between the mean water 3-10 miles away and the mean water within 3 miles of a given tract within a PUMA. Panel D shows the mean of the log house price of a PUMA in 2012.

C Calculating Counterfactual Home Prices

To compute counterfactual market clearing prices I use the Newton's Method algorithm that is used in Koijen and Yogo (2019). The price vector is determined by the market clearing function:

$$\mathbf{p} = f(\mathbf{p}). \tag{25}$$

The price vector is updated based on the slope of the market clearing function:

$$p_{m+1} = p_m + (I - \frac{\delta f(p)}{\delta p})^{-1}(f(p_m) - p_m). \tag{26}$$

Also following Koijen and Yogo (2019), I approximate the Jacobian with its diagonal elements:

$$\frac{\delta f(p_m)}{\delta p_m} \approx \text{diag}\left(\frac{\delta f(p_m)}{\delta p_m}\right). \tag{27}$$

I use a numerical derivative centered around the current price. I iterate until a tolerance level is reached. While I do not prove existence or uniqueness for my setting, demand is downward sloping and supply is upward sloping, and there is no issue with convergence to a stable equilibrium in my simulations.