The Impact of Institutional Investors on Homeownership and Neighborhood Access*

Joshua Coven†

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Abstract

Since 2012, institutional investors entered the single-family rental market in areas that subsequently experienced high rent and price growth. To determine the impact of institutional investors on the housing market, this paper estimates a structural model where institutional investor landlords benefit from economies of scale and market power. Overall, institutional investor entry resulted in a tradeoff. Renters benefited from lower rents because institutional investors increased the rental supply by 0.58 homes for each home they purchased. This expansion occurred because economies of scale outweighed the incentive to use market power to decrease supply. However, prospective homeowners had a harder time buying homes: Homeownership decreased by 0.23 homes for each home purchased, and institutional investors caused 21% of the observed price increase in their top decile of markets. Supply responses dampened these impacts. These findings show that economies of scale, not market power, are the driving mechanism behind institutional investor impact in the single-family rental market.

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†Department of Finance, Stern School of Business, New York University. Email: joshua.coven@stern.nyu.edu

I Introduction

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

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

This paper examines how institutional investor landlords differ from "mom-and-pop" landlords and quantifies the implications of these differences for the housing market. By estimating a structural model of the housing market with landlords that are heterogeneous in operating costs and market power, households, and construction, I find that institutional investor entry raised local prices by less than the observed price increases in the markets where they entered and decreased the quantity of homes available for

[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%."

homeownership by 0.23 homes for each home purchased. Despite the presence of market power, I show that large landlords increased the rental supply by 0.58 homes for each home purchased and decreased rents on net due to low operating costs at scale. Policies seeking to ban institutional investors or cap annual rent increases would increase rents by reducing the rental supply—the opposite of their intended effect on the rental market. Overall, I find that institutional investor entry benefited renters by lowering rents and increasing the quantity of rentals in neighborhoods with few rentals, but made it harder for prospective homeowners to buy homes.

I begin by describing the activity of 7 large institutional investors to motivate the mechanisms and outcomes studied in this paper. While these 7 companies owned only 0.17% of the total US housing supply as of February 2021, they were spatially concentrated: They had purchased 5.7% of the housing stock in Paulding County, which is in the Atlanta metro area, in only 9 years. The concentrated purchases raise the possibility that institutional investors locally raised prices, lowered homeownership, and added to the rental supply. On the other hand, 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. An increase in the rental supply in areas with few rentals could increase neighborhood access to those who could not afford to buy a home. Consistent with this, 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. The high local ownership concentration might also mean that institutional investors have market power which could increase rents. The descriptive evidence highlights the need for further analysis to explore the potential tradeoff between homeownership and the number of rentals in a region, as well as to establish whether the observed ownership concentration of institutional investors leads to enough market power to cause a net decrease in the rental supply.

To understand the role institutional investors play in the market, it is important to know how they differ from existing "mom-and-pop" landlords. The key difference is that 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. Small landlords 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. All else held equal, the ability to operate large portfolios at low costs could lower rents due to increasing the rental supply. However, large portfolios could allow them to gain a large share of local rentals, which can give rise to market power, which could decrease the rental supply and push rents upwards.

I develop a structural model designed to quantify the relative importance of these forces to assess the overall impact of institutional investors. The model incorporates differences in landlords' cost curves and market power in a setting where households, small landlords, and construction can respond to institutional investor entry. Key features of the model are that small landlords have decreasing returns to scale and large landlords have constant returns to scale, consistent with the empirical evidence. Constant returns to scale allow large landlords to accumulate portfolios large enough to impact rents, which gives rise to the incentive 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 decreased 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 similarly to Bayer, Ferreira and McMillan (2007), Calder-Wang (2022), and Diamond (2016) by using methods from Berry, Levinsohn and Pakes (1995) and Conlon and Gortmaker (2020). The estimation uses data from the Census American Community Survey (ACS) for prices, rents, and housing holdings. I calibrate geographic substitution patterns with bilateral migration data from Verisk (formerly Infutor). I estimate demand for different household groups based on household income. This allows me to assess not just the aggregate but also the distributional consequences of investor entry. Elasticities for prices and rents are identified with an instrumental variables (IV) strategy.

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

Rental supply in the model is determined endogenously by the sum of large and small landlords' supplies. This allows for the possibility that large landlords crowd out small landlords. I model small landlord supply as the aggregate of the decisions of individual small landlords, who choose whether to operate rentals and receive expected cash flows or sell their properties. Large landlords solve an optimization problem where they 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. Both landlord types have the same expectations about each region's rent growth based on past population growth, job growth, and state trends. This allows for the model to incorporate the incentive of large landlords to select regions with high expected rent growth, which is an alternate hypothesis of why institutional investors are associated with subsequent rent growth as opposed to the possibility that they causally raise rents through market power.

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

Institutional investor entry decreased homeownership and increased the quantity of rentals, however, supply responses lowered both impacts. Institutional investor entry decreased the number of homes available for owner occupancy by 0.23 for each home they purchased. The impact is less than 1:1 because the demand shock triggered a construction response and crowded out small landlords: Builders built 0.35 homes, and small landlords sold 0.42 homes. A back-of-the-envelope calculation that fails to consider supply responses would overestimate the investors' impact on homeownership by a factor of 4. Institutional investor entry increased the number of rentals by 0.58 for each home they purchased. This is not a 1:1 increase because institutional investors crowded out small landlords. I find evidence in the correlational data to support that these margins of adjustment are relevant: Where institutional investors entered the market, small landlords exited, builders built homes, and the rental supply increased. The model shows that low-income renters moved into the rentals supplied by the institutional investors—a finding that aligns with 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.

I find that institutional investors raised prices and lowered rents in their most concentrated regions, but both effects are below observed correlations with price and rent increases in the data. In the top decile of regions in Georgia by investor purchases, the estimation implies that institutional investors caused 21% of the observed increase in house prices. In the regions where institutional investors bought a smaller share of the housing stock, almost all of the observed local price increases would have occurred without the institutional investor demand shock. Institutional investors decreased rents by 0.7pp for every 1pp of the rental stock that they own because, on net, they increased the supply of single-family rentals. The sign of the effect of their entry on rents is opposite that of the observed correlation between institutional investor market share and rent increases.

The difference in size between the model-implied and the observed price increases, as well as the difference in sign between the model-implied and the observed rent increases, are consistent with the investors having targeted regions with expected rent and price growth to maximize returns. Invitation Homes in its initial public offering (IPO) filing described how it chose 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."[3] Consistent with this, I document that the areas where institutional investors purchased homes experienced large increases in population relative to the rest of the country after the investors' entry. The model in this paper includes the incentives of large landlords to target regions with expected rent growth and supports the conclusion that this targeting drove the association between institutional investor presence and rent growth, rather than a causal impact of institutions on rents.

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

[3] INVH form S11, page 4.

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 increases rents by a median of 0.8% in areas of overlap of the merging landlords, a magnitude consistent with that of the rent increase in Gurun et al. (2023).

I then simulate two proposed policies. One levies a tax of $10k per home per year for operators with more than 50 single-family units. This tax more than doubles 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 decrease, rents increase, and small landlords gain a large share of the homes that institutional investors are forced to sell. I also simulate a 5% cap on annual rent increases for large landlords. I find that this cap lowers the quantity of rentals that large landlords supply. The results show that not accounting for the fact that institutional investors increase the quantity of rentals leads to policies having the opposite of their intended effects on rents.

There are a number of mechanisms through which institutional investors could affect households that I do not study. 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 INVH for its use of deceptive fees.[4] Moreover, institutional investors may 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. In addition, institutional investor entry may change the amenities of a region. For example, Gurun et al. (2023) and Billings and Soliman (2024) both study the effect of institutional investors on neighborhood crime and find varied results. This paper abstracts away from the effects of institutional investors on neighborhood amenities to instead focus on how institutional investors affect homeownership and whether market power is the driving force of their impact in the rental market, which are key mechanisms of interest for policymakers who propose bans and rent increase caps.

This paper is the first to develop and estimate a structural model designed to quantify the total market-level and distributional impacts of institutional investor entry on the housing market. Several papers describe institutional investor activity in single-family

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

homes and the 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) study the effect of increasing concentration on rents, prices, and crime. Billings and Soliman (2024) study the effect of institutional investor purchases on neighboring housing prices and crime. Austin (2022), An (2023), and Lee and Wylie (2024) study the effect of institutional investors on neighborhood demographics. Gorback, Qian and Zhu (2024) study the effect of these investors on prices and rents with reduced form methods. Francke, Hans, Korevaar and van Bekkum (2023) study the effect of a ban on investor purchases by municipalities in the Netherlands on prices, rents, and neighborhood demographics.

My research makes five novel contributions to this literature. 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 not only get the size of the impact on rents wrong but also the 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' entry 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 homeownership. A back-of-the-envelope calculation of the homeownership 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 from operating single-family rentals and a 5% cap on annual rent increases and show, similarly to other research on 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 single-family landlord type that allows me to connect how the operating costs of intermediaries in real estate affect real outcomes for households. 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 school test scores.

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 multifamily rentals. Watson and Ziv (2024) study market power in multifamily rentals 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 tradeoff between rents and quantities rather than rents and vacancies. While market power 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 mergers of institutional investor landlords of single-family units to measure market power. My paper differs 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 lead to a dataset for analysis with 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 how units for multifamily properties are counted in the data.

I identify institutional investors' properties with the mailing addresses to which property tax forms are sent for each property. Following Ganduri et al. (2022), I examine mailing addresses that correspond to the most single-family rental properties in the US. I then use Google to identify the companies that correspond to the mailing addresses. In this paper, I focus on 7 companies that own the most single-family rentals 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 can identify 235,057 properties in February 2021. For the companies that were publicly traded as of 2021 (Invitation Homes, American Homes for Rent, and Tricon Residential), I 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. They are the most granular geographic unit for which the Census publicly releases yearly data rather than 5-year pooled samples. Any smaller geographic unit would require the use of tables created from 5-year averages, which would make it difficult to measure changes in prices and rents over a 9-year period, especially the years after the large price swing resulting from the Great Recession. 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 single-family completions in the Federal Reserve Economic Data up to 2018, as shown in Appendix Figure A1. To calculate 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. 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," 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.

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 to 2019. The household income groups are 0–25k, 25–50k, 50–75k, 75–100k, and 100k+.

The PUMA-level census tables include characteristics involved in the demand estimation, 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 for cleaning 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. The three asset class types are 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 January sunlight, January temperature, July temperature, and July humidity in the demand estimation as characteristics. 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 due to the presence 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

To understand the impact of institutional investors on the housing market, we need to first know where they are relevant and why they chose these locations. Therefore, 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 in the United States. The institutional investors' largest markets are Sunbelt cities including Atlanta, Phoenix, and Tampa. While they owned only 0.17% of the housing stock in the US as of February 2021, they are spatially concentrated: In Paulding County, Georgia, which is in the Atlanta metro area, the 7 companies owned 5.7% of all the housing stock. The specific location choices suggest that institutional investors are more likely to have a local impact on US cities, rather than a broad impact on the whole country, and that their investment strategy is highly dependent on geography.

I examine the characteristics of the neighborhoods where they 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 a vector of state fixed effects:

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

The results in Table B1 show that institutional investors own properties in PUMAs with low price-to-rent ratios, which make them ideal for the conversion of owner-occupied homes to rentals. This is consistent with the fact that the institutional investors studied 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 upward population and job growth pretrends. This is consistent with statements in INVH's and AMH's initial public offerings (IPO) filings which describe how they chose their markets. INVH ”selected markets that we believe will experience strong population, household formation and employment growth and exhibit constrained levels of new home construction. As a result, we believe our markets have and will continue to outperform the broader U.S. housing and rental market in rent growth and home price appreciation.”[5] Any analysis of institutional investor impact will have to separate causal impacts from their incentives to select regions with expected price and rent growth to maximize returns. Additionally, a model of investor location choice must include these targeting motives. I also confirm correlations found in other research related to their location choice. 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 relative to other PUMAs in the same state. To the extent that they created rentals in PUMAs with higher median household income, it’s possible that they increased access to desirable neighborhoods for those who cannot afford to buy a home.

Institutional investors also targeted regions that experienced many foreclosures during the Great Recession. AMH mentions in its IPO filings that this is due to low acquisition costs: ”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.”[6] Consistent with this, the regression results show institutional investors targeted regions with low prices relative to prices before the Great Recession and a high number of foreclosures per person from 2007–2011. Foreclosures were a critical acquisition channel for institutional investors early on, as documented in Mills et al. (2019) and in SEC filings from INVH and AMH. Among the properties that INVH acquired from September 2015 to September 2016, 37% were acquired through distressed sales, which shows that foreclosures and short sales played an important role in property acquisition even several years after the Great Recession. Additionally, its possible institutional investors are better able to bear risks related to buying homes from the foreclosure process. Many states have a right of redemption for foreclosures, whereby the homeowner who was foreclosed on has 12 months after the foreclosure sale to pay the purchaser to recover the property. This is 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

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

to buy 1 home to then rent. The correlation of institutional investor presence with foreclosures, as well as the data from earnings statements on the importance of distressed sales as an acquisition channel, highlight how the investors targeted regions where they could acquire homes at attractive valuation ratios.

Where they chose to enter the housing market, the institutional investors amassed concentrated portfolios of housing. In a census tract in Rutherford County, Tennessee, between Nashville and Murfreesboro, these companies own 19% of the entire housing stock: 534 of the 2803 properties in the tract. 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, which suggests that it is possible institutional investors lowered homeownership. However, households could have become homeowners elsewhere, therefore a model is needed to determine the total homeownership impact. To examine concentration, I plot the share of housing stock that 7 institutional investors own against the share of rental stock that 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 have done some combination of either expanding the rental supply or replacing existing landlords. Further analysis must determine to what extent they expanded the rental supply, which could decrease rents, and to what extent their concentration gives rise to market power, which could increase rents.

I compare the physical characteristics of the rentals that institutional investors supply with those of both other rental units and owner-occupied housing in the same ZIP code. I calculate the within–ZIP code differences between the three groups, average these differences weighted by institutional investors' ZIP code–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 ZIP codes in which they are present, as shown in Table B2. On average, the institutional investor rental supply is approximately 7.48 years newer, has 0.23 more bedrooms and 0.16 more baths, and is 20% more likely to be single-family housing than other rentals in the same ZIP codes. The institutional investor rental supply is on average 150 sq ft, or 7.6%, smaller than owner-occupied housing. This is consistent with the idea that institutional investors bought starter homes.

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

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

III.C Who Moves into Institutional Investor Rentals?

I examine whether 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. To compare the characteristics of the origin locations with those of the destination locations, I merge census tract–level data on median incomes, middle-school math test scores, and historic economic mobility from Opportunity Insights for both sets of locations. In Table 1, I show the mean differences between destination and origin census 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% higher likelihood of incarceration, and a 3.4% lower likelihood of a resident to enter the top income quintile. To the extent that the institutional investors increased rental supply, they did so in areas with better schools and economic mobility than the origin locations of the renters who moved into those investors' units.

To isolate whether institutional investors' market presence not only increased the quantity of rentals in good locations but also changed the flow of people to those locations, I compare the renters who moved into institutional investor homes with those who moved into other homes in the same census tract. For the subsample of all movers into census tracts with institutional investor homes, I create a dummy variable to flag those who moved into an institutional investor home for the first time, and I regress origin census tract characteristics on this dummy variable with destination census tract fixed effects. The 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 investor entry increased access to the neighborhood for people coming from worse areas.

III.D Differences Between Small and Large Landlords

To determine whether institutional investor entry affected the housing market, we need to understand how institutional investors differ from the single-family landlords already present in the market and how the differences might matter for the housing market. The first difference is that institutional investors are much larger than the majority of single-family rental operators. I construct operator-level single-family rental portfolios from the Verisk property data in February 2021 and show the fraction of all single-family rentals owned by operators of different size buckets and whether the operator is present in one county or multiple in Figure 2 Panel A. Institutional investors entered an extremely fragmented market dominated by "mom-and-pop" landlords: 71% of single-family rentals are owned by operators with 1–3 properties and 75% by operators who do not operate in multiple counties. Institutional investors, some of which own over 80,000 units, are much larger than the small landlords that make up most of the market. Differences in size enable spatial concentration in ownership, which is not possible for operators with 1–3 homes. While landlords with portfolios of 1000+ units, even in 2021, own only 1.8% of single-family rentals, the spatial concentration of institutional investors, as shown earlier in Figure 1 Panels A and B, makes them relevant operators in the regions where they own housing. Large portfolios could lead to economies of scale, which could allow investors to increase the rental supply and lower rents. However, spatial concentration could allow for market power, which could raise rents.

Economies of scale lower institutional investor landlords' operating costs relative to those of small landlords. Figure 2 Panel B compares cost components for average small landlords from the RHFS to cost components from earnings statements for INVH and AMH, which I call the "large average." Institutional investors have lower property taxes as a share of rent. This may be because institutional investors are more likely to appeal their property tax assessment valuations, as documented in Austin (2022). Institutional investors also have lower operating expenditures. AMH's IPO filing mentions that it obtains quantity discounts for materials regularly used, including paint, flooring, and blinds. INVH's IPO filing mentions that it can obtain discounts for HVAC systems and contractor discounts by working directly with vendors on projects for which it does not use in-house staff. Large landlords have much lower insurance costs, at 1–2% of rent rather than 5–6%. Large operators bargain with insurance companies for a bulk discount here as well.

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

Large landlords have more debt and pay lower interest rates than small landlords. In the RHFS, 63% of small landlords do not have mortgages or similar debt. In the Verisk data, 57% of small landlords do not have a mortgage. Large landlords have higher levels of debt. In 2021, INVH had a debt-to-value ratio of 51% and AMH 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 landlord–owned homes, owner-occupied homes, and the weighted average interest rates on debt for INVH and AMH in Figure B3. There is an interest rate spread between new mortgages for owner-occupants and small landlords of approximately 0.2%. The spread is larger for existing mortgages, at approximately 0.5%. AMH and INVH have significantly lower costs of debt than small landlords and owner occupants. INVH in particular has a lower cost of debt than AMH, possibly due to shorter term lengths.

Small landlords minimize cash costs in a way that does not scale, suggesting that they have decreasing returns to scale. 83% of small landlords do not use professional managers, 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 becomes harder for one 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 more likely to have a mortgage than low-cost small landlords. Therefore, a move from not having a mortgage to having a mortgage would likely move a small landlord to a higher cost bucket in the histogram, which suggests decreasing returns to scale. Additionally, small landlords who purchased homes recently are more likely to have a mortgage than those who purchased decades ago: Figure B4 Panel A buckets landlords in the RHFS 2021 vintage by when they purchased a home, and it shows the fraction of each bucket that has a mortgage. Panel B shows the fraction of the original mortgage balance remaining by purchase year for those who still have mortgages. Small landlords appear to obtain mortgages with loan-to-value (LTV) ratios of approximately 80%, similarly 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 that they are more likely to have higher mortgage balances and therefore higher interest expenses, which suggests decreasing returns to scale within operator. Additionally, Fannie Mae's mortgage underwriting liquid reserve requirements increase for additional investment properties up to 10, so financing constraints increase with the number of properties in the size range relevant to the majority of single-family rental operators.[7]

Large landlords appear to have better returns to scale. While there are no data on INVH's and AMH's costs before they went public, I can examine how changes in their scale affected their cash costs after they became public companies. First, I examine INVH's market-level average operating expenses per home against the market average number of homes in Figure B5. There is no association between the number of homes and operating expense per home. I examine variation in portfolio size due to a merger to obtain

[7] Fannie Mae minimum reserve requirements.

a different look at how operating expenditures per home might vary with portfolio size. In 2017, INVH bought Starwood Waypoint Homes, and its portfolio size rose from 50,000 to 82,000 homes. In Figure 3 Panel B, I plot the change in operating expenses per home against the change in number of homes from this merger for each market. The black dotted line represents no change in operating expenses per home. While this variation is not exogenous because they may choose to expand in areas where they expect operating expenses to decrease for other reasons, the figure suggests that INVH can almost double the number of homes that it has in a market without raising its operating costs per home. Most likely, the companies experienced increasing returns to scale early on as they paid fixed costs to build capabilities for management, acquisition, and renovation, and then, in later stages, their returns to scale became constant, and would eventually decrease if they grew large enough. The variation that I observe suggests that the assumption of constant returns to scale is reasonable for the the number of homes in the range around the merger quantities—the relevant region for model simulations.

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 constant returns to scale over a large range of quantities, I incorporate these facts in a stylized model of the single-family rental market to illustrate the economic channels through which institutional investor entry can affect the housing market. Figure 4 Panel A shows the supply and demand curves for single-family rentals in one region. As motivated by the earlier section, I model household demand as downward sloping, small landlord supply as upward sloping, and large landlord supply as constant. Here, if the large landlords choose competitive quantities, the equilibrium moves to the right from A to B: Rent decreases and the number of rentals in the region increases.

To illustrate the market power channel in this stylized example, I assume that 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 that its quantity choice has on rent, leading to market power. I show this in Figure 4 Panel B. The large landlord chooses the profit maximizing quantity, at which the residual marginal revenue intersects its cost curve. This shifts the equilibrium left to C: rents increase and quantities decrease compared to B. The movement from B to C is the effect of market power, which is derived from the institutional investor's cost advantage arising from scale and spatial concentration.

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

Supply and demand for single-family rentals are modeled as a Cournot oligopoly (Cournot, 1838) where small landlords are price takers and large landlords choose quantities to maximize prices. Two features of the single-family rental market make Cournot competition fitting for this setting. First, single-family rental units are highly liquid relative to other real estate assets: It is easier to sell a piece of a single-family portfolio than a piece of a multifamily portfolio because the discrete units are smaller. In addition, institutional investors can sell to both households and landlords, providing an additional source of exit liquidity. Thus, rather than raising rents and increasing vacancies, it can sell vacant units or buy fewer units in the first place. Second, there are no barriers to entry: If an institutional investor sells a home, another landlord can operate it if doing so is profitable. If rents rise sufficiently, a small landlord can buy a home from a homeowner or landlord and then offer it as a rental. Both the liquidity and lack of entry barriers make the Cournot model ideal for the single-family rental market. These features contrast with characteristics of the multifamily rental market, which is less liquid due to larger property sizes and lower homeowner involvement, where the tradeoff for exerting market power is between raising rents but also vacancies.

IV Model

To estimate the equilibrium impact of institutional investor entry, I add to the stylized model an integrated rental and ownership market, construction, and multiple PUMA-level regions to and from which households can move. 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 by comparing expected operating cash flows to the amount of cash that they would obtain from selling their properties. In aggregate, they have decreasing returns to scale, as discussed in the previous section. Large landlords choose a number of rentals to operate in each region. They are large enough to internalize the impact of their quantity choices on equilibrium rents 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 that 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 investor presence on homeownership that does not account for this household would overstate the impact. Second, the model lets me compare economic channels to see what drives the net effects. This is important because natural experiments based on 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 investor entry on rents. Third, the model can quantify economic channels to estimate, for example, how much larger the impact on prices would have been in the absence of a construction response. Fourth, the model allows for policy simulation.

The model, by construction, excludes unmodeled mechanisms. This helps isolate the impact of institutional investor entry because the model excludes the population increases that occurred in institutional investor PUMAs that were unrelated to institutional investor entry and that may have affected prices and rents. However, it also excludes possible mechanisms for investor impact such as changes to home or neighborhood quality. For example, if institutional investors renovate properties, this could increase demand for these properties and therefore increase rents. If rents rise because of renovations, it is not clear that this is negative for renters, in contrast to market power–induced decreases in quantities and increases in rents with no change in the quality of rentals. There is varied evidence on the effect of institutional investors on neighborhood crime. Gurun et al. (2023) show that a merger between institutional investors decreased crime, while Billings and Soliman (2024) show that areas where institutional investors purchased homes experienced increases in crime. While changes to neighborhoods are important for households, this paper focuses on whether institutional investor entry decreased the number of homes available for owner occupancy, whether institutional investors' market power caused a net increase in rents, and how their presence affected market-level prices and rents.

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, 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 a single-family unit, or rent a multifamily unit in that location. The discrete-choice model is similar to the models in 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. This income heterogeneity allows for heterogeneity in price and rent elasticities. The heterogeneity in origin location allows for realistic spatial substitution patterns.

A household from origin location i in income group h in asset class l, where the asset classes are owned housing, rented single-family housing, or rented multifamily housing, solves a discrete-choice problem to determine where to move, j (the choice could also be not to move if $j = i$), and which asset class k to live in at the destination. The household maximizes utility based on characteristics of the destination location and asset class, $X_{j,k}$, and a utility cost of moving from location i asset class l to location j asset class k: $\tau_{(i,l)\to(j,k)}$. 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 $k = owneroccupied$, of single-family-unit rent if $k = rent_{sf}$, or of multifamily-unit 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:

$$u_{h,(i,l)\to(j,k)} = \beta_{h,k,0}p_{j,k} + \beta_{h,k,d}X_{j,k} + \tau_{(i,l)\to(j,k)} + \xi_{h,j,k} + \varepsilon_{h,(i,l)\to(j,k)}. \tag{2}$$

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

$$w_{h,j,k} = \sum_{i,l} \frac{\exp(u_{h,(i,l)\to(j,k)})}{1 + \sum_{(m,s)} \exp(u_{h,(i,l)\to(m,s)})} w_{h,i,l}. \tag{3}$$

$X_{j,k}$ includes characteristics related to climate (January temperature, January sunlight, July temperature, July humidity), the physical housing stock (median year built, median number of rooms, median fraction of the PUMA that is single-family housing), amenities and schools (fraction of the population with a commute under 45 minutes, log distance to nearest MSA, log distance to nearest top-30 MSA, fraction of the high-school-aged population in high school, fraction of the high-school-aged population in private school), and topography (average amount of land within 3 miles unavailable for construction because of water, wetlands, and total unavailable land), along with year fixed effects. 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 data on any variable in $X_{j,k}$ 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 accurately capture geographic substitution, I allow each income group to have within-group heterogeneity by origin location. Each origin asset class and destination asset class pair has a different utility "cost" of moving: $\tau_{(i,l)\to(j,k)}$. This is a function of the pairwise distance, the number of social connections from Meta's Social Connectedness Index (SCI) as used in Bailey, Cao, Kuchler and Stroebel (2018), and a dummy variable for all possible transitions between owning, renting single-family, or renting multifamily housing interacted with a dummy variable for whether the household stays in the same PUMA. The next section will provide more details on the estimation of this moving cost.

Heterogeneity in moving costs results in the propagation of the institutional investor impact along a network based on empirical moving patterns, similarly to how housing market shocks propagate along search networks in Piazzesi, Schneider and Stroebel (2020). Diamond (2016) models household demand with birth-state heterogeneity. Dynamic housing models estimated directly from migration data such as those in Schubert (2021) and Almagro and Dominguez-Iino (2024) obtain accurate spatial substitution by estimating discrete choice models with migration shares for different household types as a function of their characteristics, rather than this paper which uses holdings data for different income groups. My method in this paper combines migration data that do not have heterogeneity in household types with cross-sectional location data that do have heterogeneity in income to obtain realistic spatial substitution in a static model with heterogeneous households.

The portfolio weights for each household group sum to 1:

$$\sum_{(i,l)} w_{h,i,l} = 1. \tag{4}$$

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

$$Q_{d,households,i,l} = \sum_h w_{h,i,l} N_h. \tag{5}$$

IV.B Small Landlord Demand

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

$$E\left[\sum_t \frac{(R_{j,t} - C_{i,j,t})}{(1+r_e)^t}\right] \geq P_{j,t} \times (1 - BrokerFee) - M_{i,j,t}. \tag{6}$$

The left-hand side is the expected operating cash flows in each period $R_{j,t} - C_{i,j,t}$ discounted by the cost of equity for those cash flows r_e. The right-hand side is the cash a landlord would obtain from selling a home. The landlord receives 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 and job growth in the region, and state-level trends. The cost for a landlord i in a region j is:

$$C_{i,j} = P_j \times PropTax_j + InterestExpense_{i,j} + OtherCosts_i + R_j \times ManagerFee_i. \tag{7}$$

In Figure B4, I show that small landlords in the RHFS pay off their mortgages over time. Panel A shows that the fraction of small landlords with mortgages decreases with the 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 the 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 is paid off over 30 years, is aware of its expected payoff behavior and takes this into account when deciding whether to operate. These assumptions allow the model to capture the fact that some small landlords might barely break even when first purchasing a property because they expect to pay off their mortgage to have larger cash flows in the future. I model small landlords' interest expense as the perpetuity equivalent of the present value of their interest payments. This leads to the decision to operate to be formulated as:

$$R_j \geq (r_e - g_j) \times (P_j \times (1 - BrokerFee) - M_{i,j,t}) + C_{i,j}. \tag{8}$$

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

$$Q_{d,small,j} = \sum_{i \in N_{small,j}} I\left[R_j \geq (r_e - g_j) \times (P_j \times (1 - BrokerFee) - M_{i,j,t}) + C_{i,j}\right]. \tag{9}$$

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 because of the heterogeneity in costs of the underlying individual landlords. The heterogeneity in costs that leads the returns to scale to be decreasing is driven by different interest and operating expenses.

IV.C INSTITUTIONAL INVESTOR DEMAND

I model large landlord demand for homes in a region, rather than set demand equal to the observed quantities in the data, to obtain demand that varies with parameters and market structure. This choice allows me to model large landlord demand changes due to mergers or caps on rent increases. A large landlord i chooses a quantity of homes to buy in region j, $Q_{i,j}$ to maximize profits if the region experienced above median foreclosures in its state during the Great Recession:

$$\max_{Q_i} \{Q_i \times (CashFromOperating - CashToBuy), 0\} \tag{10}$$

$$s.t.\ \ ForeclosuresPerUnit_j \geq Median_{state}(ForeclosuresPerUnit_j).$$

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 supplied by others in the market, Q_{other}, who include small landlords and other large landlords. Large landlords purchase each home with debt D_t equal to the company-level debt-to-value ratio times the property price:

$$CashFromOperating = E\left[\sum_t \left(\frac{R_{j,t}(Q_{other}+Q_i) - C_{i,j,t}}{(1+r_e)^t}\right)\right] \tag{11}$$

$$CashToBuy = P_{j,t}(Q_{other}+Q_i) \times (1 + renovationCost) - D_t \tag{12}$$

$$C_{i,j} = P_j(Q_{other}+Q_i) \times PropTax_j + IntExp_i + OtherCosts_{i,j} + ManagementCosts_i. \tag{13}$$

Region-specific costs depend on the local property tax rate. Large landlords' region-specific operating costs are a function of local contractor wages. In contrast to small landlords, large landlords have non-region-specific interest expenses and management costs.

Large landlords have the same expected cash flow growth rate as small landlords, g_j, which allows me 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 but not small landlords.

The mechanism through which market power affects rental quantity in this setting is different from that in a multifamily rental market. In multifamily rental markets, market power results in a tradeoff between higher rents and lower occupancy, as in Calder-Wang and Kim (2024) and Watson and Ziv (2024). Because single-family homes are a more liquid asset than rental units in multifamily properties, if the institutional investors want to lower the quantity supplied, they can simply sell homes rather than leave them vacant or not buy homes in the first place. This greater liquidity stems from two factors: Single-family units are smaller and so part of a portfolio can be sold more easily, and they can be sold to either landlords or owner-occupants. I show the occupancy rates for INVH's markets in Figure B6. Occupancy rates fluctuate here by up to 4 percentage points (pp) from 95% to 99%. They increased sharply after the onset of the COVID-19 pandemic, when many people moved out of cities, as documented in Gupta, Mittal, Peeters and Van Nieuwerburgh (2022) and Coven, Gupta and Yao (2023). They did not change substantially around the date of INVH's merger with Starwood Waypoint Homes. High occupancy rates that move because of trends unrelated to mergers, coupled with the difference in liquidity between single-family and multifamily homes, suggest that the mechanism giving rise to market power here is not rising rents and increasing vacancies. 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 because of 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:

$$\log\left(\frac{Q_{j,own,new}}{Q_{j,own,2012}}\right) = \max\left\{\gamma_j \times \log\left(\frac{P_{j,own,new}}{P_{j,own,2012}}\right), 1\right\}. \tag{14}$$

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

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

The supply of rentals in each region j is determined by the demand of small and large landlords to own homes and operate them:

$$Q_{s,j,rent} = Q_{d,j,smalllandlords} + Q_{d,j,largelandlords}. \tag{15}$$

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:

$$\mathbf{p} = f(\mathbf{p}) = \log\left(\mathbf{P}\cdot\left(\mathbf{Q}_{d,\text{households}} + \mathbf{Q}_{d,\text{small landlords}} + \mathbf{Q}_{d,\text{large landlords}}\right)\right) - \log(\mathbf{Q}_s). \tag{16}$$

For rentals, $Q_{d,large\ landlords} = Q_{d,small\ landlords} = 0$ 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 then estimating elasticities to prices, rents, and characteristics for each group with the methods from Berry et al. (1995) and Conlon and Gortmaker (2020). The household demand estimation uses cross-sectional variation from a pool of census PUMAs and bilateral migration data for the whole US from 2012 to 2019.

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

$$w_{(i,l)\to(j,k)} = \beta_{p,k} p_{j,k} + \beta_{x,k} X_{j,k} + \beta_t T_{(i,l)\to(j,k)} + \varepsilon_{(i,l)\to(j,k)}. \tag{17}$$

The origin–destination pair characteristics $T_{(i,l)\to(j,k)}$ include distance, the social connectedness index value for the pair of PUMAs, and interactions between all possible asset class transitions and a same-PUMA indicator variable. The destination characteristics are the same as in the estimation of migration costs and household demand, as detailed in the previous section. I estimate equation (17) 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 them to create the moving costs in utility terms:

$$\hat{\tau}_{(i,l)\to(j,k)} = \beta_t T_{(i,l)\to(j,k)}. \tag{18}$$

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

$$u_{h,(i,l)\to(j,k)} = \delta_{h,j,k} + \hat{\tau}_{(i,l)\to(j,k)}. \tag{19}$$

Equation (3) becomes:

$$w_{h,j,k} = \sum_{i,l} \frac{\exp(\delta_{h,j,k} + \hat{\tau}_{(i,l)\to(j,k)})}{1 + \sum_{(m,s)} \exp(\delta_{h,m,s} + \hat{\tau}_{(i,l)\to(m,s)})} w_{h,i,l}. \tag{20}$$

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

$$\hat{\delta}_{h,j,k} = \beta_{h,p,k} p_{j,k} + \beta_{h,x,k} X_{j,k} + \xi_{h,j,k} + \varepsilon_{h,(i,l)\to(j,k)}. \tag{21}$$

I constrain $\beta_{h,p,k} < 0$ to ensure that demand is downward sloping. If two PUMAs are identical except for price, an agent would prefer the cheaper one. An estimation that results in an agent favoring PUMAs with higher prices can be interpreted as prices co-varying with something desirable to households that is outside the model. I estimate equation (21) separately for each income group for the panel of yearly housing holdings from 2012 to 2019 from the census PUMS data in a pooled regression. I do this on the extensive margin by adding one household to each region, resulting in tiny weights in regions where a given household group does not rent or own.

Identification. I estimate both equations (17) and (21) with linear IV. $p_{i,l}$ 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 upward. I instrument for the prices and rents in a PUMA with features of the housing stock and topography of neighboring regions, similarly 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, the characteristics of neighboring regions matter through a competition channel but, once own-region characteristics are controlled for, do not affect a household's utility from living in that PUMA because those neighboring regions are sufficiently far away.

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

I show the first stage of the IV regression of equation (21) in Appendix Table B3. The 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 the within-3-mile PUMA area have signs opposite those of the corresponding features for the 3–10 mile ring. Greater land unavailability in neighboring regions is associated with higher rents, illustrating the competition channel: If it is harder to build nearby, rents are higher. For log prices, land unavailability in neighboring regions due to water is associated with higher prices, and the variable has the opposite sign of land unavailability due to water within 3 miles. The statistical significance and opposite signs suggest that neighboring regions' characteristics are relevant and affect price and rent through a different channel from the one through which PUMA characteristics affect price and rent.

I examine the instrument spatially in Figure B7. Panel A shows the mean land unavailability due to water within 3 miles for each PUMA in Georgia, Panel B the mean land unavailability due to water 3–10 miles away, Panel C the difference between Panels B and A, and Panel D the log house prices in each PUMA. PUMAs near the city center have greater land unavailability due to water in neighboring regions than land unavailability due to water in their own region. This 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 explanation for this correlation in the regression for the whole US could be that cities develop near ports and on land appropriate for building but close to land not suitable for construction because of water and that the 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 that of own topography on prices and rents must remain after proximity to city centers is controlled for.

Estimation results. Table B4 shows the estimation results for equation (17). People are more likely to move to nearby PUMAs with a high social connectedness index value than to more distant PUMAs with fewer social connections. People are most likely to stay within the same asset class and within the same PUMA.

Figure B8 shows the moving elasticities for each income group with respect to prices and rents from the estimation of equation (21). There is substantial variation in moving elasticities with respect to prices and rents by income group. For both housing prices and rents, the elasticity decreases with income. These elasticities reflect the percentage of a group that will leave for a different PUMA, not the percentage that will leave a house. The model abstracts from downgrades 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 elasticities are for moves to different PUMAs. Therefore, the elasticities will be lower in magnitude than elasticities for housing units. I expect that, as the size of the geographic unit increases, the elasticity of a group to housing prices in that unit decreases. For example, it is easier to leave a neighborhood if neighborhood prices increase than to leave the country if the country's prices increase. Approximately 80% of US counties have a population less than the minimum PUMA population,[8] and therefore, a household leaving its PUMA would in most cases be making a larger move than a household leaving its county. The moving elasticities are sufficient to study the question of how institutional investors increased prices in an entire PUMA. Functionally, low moving elasticities for high-income groups mean that, in the model, when large landlords shock the market, residents making 100k+ will not leave for a different PUMA. I show the full estimation results for rental housing in Table B5 and for owner occupied housing in Table B6. Residents making 100k+ are constrained to have a $\beta_p,\ \beta_r = -0.001$ to ensure they have downward sloping demand.

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

V.B Small Landlord Demand

I calibrate the small landlord demand for each region in equation (9) by sampling from the 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 (9) 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 $PropTax_j$. This 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 property data and select properties purchased in 2012 or earlier because the November 2015 cross section is the earliest 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 the PUMA-level average mortgage balance outstanding as a percentage of the sale price in Figure B9. 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 to 2012 at the PUMA level on an indicator variable for above-median national population growth from 2006 to 2012, an indicator variable for above-median annual job growth from 2004 to 2013 from the Opportunity Insights data, and state fixed effects:

$$g_{j,s} = \beta_{pop} I\left[\Delta pop_{j,s} \geq Med.\Delta jobs_{j,s}\right] + \beta_{jobs} I\left[\Delta jobs_{j,s} \geq Med.\Delta jobs_{j,s}\right] + \alpha_s + \varepsilon_{j,s}. \quad (22)$$

I recover $\beta_{pop} I\left[\Delta pop_{j,s} \geq Med.\Delta jobs_{j,s}\right]$, $\beta_{jobs} I\left[\Delta jobs_{j,s} \geq Med.\Delta jobs_{j,s}\right]$, and α_s for each PUMA and then set the mean of this resulting distribution to 4%—the 5-year expected rent growth from the New York Federal Reserve Bank's Survey of Consumer Expectations (SCE) data for 2014, the earliest year of publicly available SCE data. This process yields an estimation of expected rent growth that is the sum of the mean national expected rent growth and an approximate 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, that the relationship of these variables with rent will stay the same, and that state-level trends will stay the same. Both small and large landlords have the same expected rent growth. 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 PUMA's small landlords, I sample from this distribution operating costs excluding interest and property taxes $N_{small,j}$ times to obtain the PUMA landlords' operating costs and manager fees as a function of region-specific rent. For all PUMAs, I set $BrokerFee$ to 6%, which is standard.[9]

To obtain r_e, I assume that small landlords have the same asset betas as INVH and AMH from their IPOs to 2024, and I set their required rate of return to what it would be if they had zero leverage. I obtain this from applying the capital asset pricing model (CAPM) to the unlevered total return betas from INVH and AMH, which leads to 5.2%, a figure that 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 expenses. If we excluded all interest expenses and set the discount rate to 0, there would still be some landlords who are unprofitable. When I include interest expenses and consider the opportunity cost of money tied up in the property, I observe that a larger number of landlords in the data are operating at an apparent loss.

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

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 the 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; I call these high-investor-activity regions. The results are in Table B7. The estimated quantities are highly correlated with the actual ones. The quantities are underestimated for both Georgia and the subset of Georgia PUMAs where institutional investors are most active. The estimation is more accurate in regions with high institutional investor activity. Overall, the model cannot 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 take observed small landlord costs, drop interest expenses entirely, and use a discount rate of 0, I observe landlords who should not be operating. Thus, it is not surprising that my procedure underestimates the landlords who operate. The estimation is more accurate for areas where rent-to-price ratios are high. There are a few reasons why small landlords might have a greater propensity to operate rental properties than expected by considering net present values. First, they have option value to use the home for personal use some day. Second, they have control rights. Third, if a large number of small landlords are retirees, they might value stable cash flows more than the CAPM would suggest. I make up for the underestimation of the number of small landlords in operation by inserting a residual Ξ_j so that the model matches the 2012 housing market exactly:

$$Q_{d,small,j} = \sum_{i \in N_{small,j}} I\left[R_{j,t} \geq (r_e - g_j) \times (P_{j,t} \times (1 - BrokerFee) - M_{i,j,t}) + C_{i,j,t}\right] + \Xi_j. \tag{23}$$

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. The elasticities for PUMAs with high investor activity, for which the estimation is more accurate, are not too far from elasticities for all of Georgia and are more relevant for the model counterfactuals.

I examine the fitted elasticities as a function of parameters in the calibration with a regression in Table B8. 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. Small landlords' sensitivity to price decreases with high expected rent growth decreases and increases with high price-to-rent ratios and high PUMA leverage. PUMAs with many institutional investors have low price to rent ratios and high expected rent growth, therefore the small landlords in these regions are less sensitive to prices.

V.C Large Landlord Demand

I calibrate large landlord demand for each region using cost data from earnings statement supplements. I repeat equation (11) 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 AMH'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 (BLS) Quarterly Census of Employment and Wages. I use a renovation cost of 5%. For the debt fraction, I use the 65% debt-to-value ratio from INVH's early time periods. I choose r_e to be 16%. After talking with operators, 16% seems like a reasonable hurdle rate given that internally some of the operators target IRR's of up to 20%. While the IRR is not a hurdle rate, a company targeting a given IRR may select to use it as a hurdle rate. A discount rate of 16% helps the model match the aggregate number of large landlord units to the data. Scaling this number up or down changes this aggregate but does not change where in Georgia the institutional investors choose to operate. Given the importance of foreclosures in large landlords' choice of which homes to purchase, I allow large landlords to purchase homes only in PUMAs with above median foreclosures per unit from 2007 to 2011 within the state.

I show the large landlord estimation results spatially in Figure B11. Panel A shows the estimated quantities for 3 identical large landlords and Panel B 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 a significant presence. The spatial pattern is similar for both the estimated and actual quantities. The estimated total number of units in Georgia is 20,000 and the actual number is 22,000. The model overpredicts 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 census tract–level elasticities to the PUMA level to obtain γ_j. First, I map census tract identifiers from the 2000 version of census geographies to the 2010 census geographies. The elasticities are then aggregated to the PUMA level with a weighted average by the number of homes in each tract. This procedure yields a supply elasticity that is heterogeneous in each PUMA and depends on the elasticities in the census tracts that make up the PUMAs. I show the supply elasticities for new units for Georgia in Figure B12. 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 was 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 investor entry on the number of homes available for homeownership. The 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, this puts downward pressure on the number of homes for owner occupancy by 1. However, the institutional investor demand shock triggers a supply response: For each home the institutional investor's purchase, builders build 0.35 homes, and small landlords sell 0.42 homes. A back-of-the-envelope calculation of the impact of institutional investors on homeownership that fails to incorporate the supply responses would overestimate the impact by a factor of 4. On the other hand, institutional investors increase the number of homes available to rent by 0.58 homes for each home that they purchase. The estimation, which includes both the incentive to use market power and the operating efficiency of land landlords, results in a net increase in rental supply. This shows that the economies of scale outweigh the incentive to use market power to decrease rental supply. In Panel B, I show that the increase in rental supply is less than 1:1 due to the crowding-out of small landlords, who sell 0.42 homes.

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

$$\Delta Q_{other,cty,tr} = \Delta Q_{i,cty,tr} + \alpha_{cty} + \varepsilon_{cty,tr}. \tag{24}$$

Results for specifications with varying fixed effects for both the extensive and intensive margin, where institutional investors gained properties over this period, are reported in Table B9. Each unit institutional investors gained is associated with other landlords decreasing their holdings by 0.53-0.69 units. This non-causal correlation is larger than the model implied impact of institutional investors on small landlords of 0.42, possibly because prices rose in these regions for reasons unrelated to large landlord entry. In both the model and the correlational data, when institutions enter, other landlords exit but not 1:1, so the rental supply increases. Next, I examine which types of landlords leave tracts by running the same regression except the dependent variable is the change in units for a specific landlord type. Landlords types are based on portfolio size and the smallest landlords are split into small landlords with mortgages and those without. Results are in Figure B13. When institutional investors increase their holdings, the other largest landlords tend to decrease and small landlords with mortgages tend to leave. The largest other owners tend to decrease their holdings because institutional investors merge and buy from other large landlords, and also because they buy foreclosed homes which can appear in the data as coming from large portfolios of foreclosed homes. The smallest landlords with mortgages leave, which is consistent with the model predictions that highest cost small landlords, those with mortgages, would be the first to leave as prices increase. I also examine who institutional investors buy from directly. While I do not have transaction-level data, the property-level data contain information related to the most recent sale of each property. I am able to examine 17,000 purchases by institutional investors from 2017–2021 and find that 44% of their purchases are from owner occupants and 56% are from non-owner occupants. This is consistent with results in Gorback et al. (2024) who find that institutional investors buy 39% of their properties from owner occupants and 61% from non-owner occupants. Both the regressions and the transaction analysis support the model results that institutional investors increase the rental supply and crowd out other landlords.

I examine whether the rentals that the institutional investors supply increase neighborhood access for the financially constrained. I plot the model output of the number of owner-occupied homes and rentals that each income group gains or loses when the institutional investors enter in Figure 6. Households with incomes between $25k and $50k lose the most homes for owner occupancy because homeowners with incomes in this range are most exposed to the institutional investor shock. By supplying rentals, the institutional investors increase the rental supply for the lowest-income renters, whose elasticity to changes in rents is highest. The results are consistent with the descriptive analysis, which showed that the renters who moved into institutional investor homes came from areas with lower median household incomes.

The institutional investor demand shock increased prices by 1.9pp per 1 pp of the total housing stock in a PUMA purchased. In Figure 7 Panel A, I plot the model-implied impact of institutional investor entry on home purchase prices by the share of a PUMA's housing stock that the institutional investors purchase. I also plot the binscatter of the association of institutional investor entry and actual price increases in excess of the rest of the US from 2012 to 2019. The model-implied impact is significantly smaller than the data association, suggesting that the investors targeted regions where prices would have gone up had they not entered. 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 top decile of PUMAs by institutional investor purchases, prices increased by 7.4%, which on a $300k home is $22,200. The model-implied impact is not monotonically increasing in the institutional investor share because each PUMA has a different price elasticity because of the heterogeneity among the PUMA's residents and a different supply elasticity. For the majority of regions where institutional investors entered, almost all of the observed price association is not attributable to these investors. Additionally, these investors entered only a small portion of the country and are not responsible for the broad price increases in the US over this time period.

Institutional investor entry decreased rents on net because they increased the supply of rentals. I show the model-implied impact of institutional investor entry on single-family rents in Figure 7 Panel B. The x axis shows the share of a PUMA's single-family rentals supplied by institutional investors after entry. Institutional investors decreased rents by 0.7pp per 1 pp of the total rental stock that they own. The model-implied rent impact is of opposite sign to that observed in the data, suggesting that rents would have risen in the institutional investors' absence. This impact incorporates both the investors' market power and their operating efficiency. The investors are sufficiently efficient operators that even with market power, they increase the number of rentals and decrease rents. If policymakers were to consider only the market power channel, they would get the direction of institutional investors' impact on rent wrong.

Institutional investor entry caused a price increase that led to capital gains for owner-occupants throughout the period of this price increase. In the model, I calculate the capital gains of groups of households attributable to the price increase caused by institutional investors, and I plot these model-implied capital gains in Figure 11. The highest-income and middle-income households obtain the most capital gains because of the combined effects of differential exposure to the investors and differential likelihood of leaving across income groups. The middle-income groups are the most exposed but are also more likely to sell their homes, while high-income homeowners are not as exposed but do not move at all in response to the demand shock.

I examine whether it is likely that the observed price and rent increases in regions where institutional investors entered are attributable to institutional investors' targeting of regions where prices and rents would have risen without their entry. In the ACS, I examine the change in the number of households from 2012 to 2019 when compared with the number of homes institutional investors owned in a PUMA and plot this association in Figure B2 Panel C. Compared to the rest of the country, the areas where institutional investors purchased homes experienced outsized population gains. In their IPO filings, the investors indicated that they targeted areas with expected population growth in anticipation of correspondingly higher price and rent appreciation. The shape of the population curve matches the shape of the price and rent associations in Panel A, suggesting that population growth, not the presence of institutional investors, caused the price and rent increases. If institutional investors had caused the increases, we would expect to instead see monotonically increasing prices and rents with institutional investor concentration.

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 PUMA with institutional investor overlap, single-family rents increase by 0.8%. This effect is increasing in the share of rental housing owned by the institutional investors. The magnitude of the effect through this channel is consistent with that measured in Gurun et al. (2023), which uses quasi-experimental variation from mergers of large landlords and finds a rent impact of 0.5% in the region of overlap. The effect may be larger due to the lack of adjustment costs in my setting. The market power here is due to the merged 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 0.57% in the regions with overlap between the merged companies 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 be 2.8 times as large if there were no construction response: 5.2 pp per 1 pp of housing stock purchased by the institutional investors in a PUMA. This suggests that supply responses play an important role in mediating the price impact. Similar-sized demand shocks to regions with less elastic supply would cause larger price impacts.

VI.C Policy Simulations

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

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

I estimate the structural model of housing demand and supply to match 2019 exactly, and then I remove the 7 large landlords from the descriptive analysis from the homes in their exact footprint from 2019. Next, I observe market-clearing prices, rents, and quantities for Georgia. I show the impact on prices in Figure 10. Prices decrease by 9.6pp per 1pp of the housing stock that institutional investors own, and rents increase by 1pp per 1pp of the rental housing stock in a PUMA that they own. Among the homes vacated, 57% go to small landlords. The End Hedge Fund Control of American Homes Act requires that large landlords sell only to households, not landlords. This would lead to all of the homes going to households, but the price decreases and rent increases would be even larger.

I also simulate a 5% annual rent increase limit for corporate landlords by taking the estimated structural model for 2012 and capping the expected rent growth for large landlords at 5%. I find when institutional investors enter the market with this rent cap, they buy 12% 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 large landlords expect this cap to be binding because large landlords decrease quantities in regions.

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

VII Conclusion

This paper estimates the impact of institutional investors entering the single-family rental market for the first time since 2012. It develops a structural model with landlord type heterogeneity in operating costs and market power, and then simulates institutional investor entry into the housing market where households, small landlords, and construction can respond. I find that institutional investors increase the quantity of rentals and lower rents on net because their ability to operate large portfolios at scale outweighs the incentive to use market power to decrease the rental supply. Institutional investors decrease the quantity of homes available for homeownership and raised prices, however the homeownership impact is 1/4th of what it would be if there were no supply response and the price impact is far below the observed association between institutional investor purchases and actual price increases. I find that renters from regions with lower median incomes, worse school test scores, and lower historic economic mobility move into institutional investor rentals. Together the results suggest that institutional investors lowered rents for renters and increased their neighborhood options, caused capital gains for incumbent homeowners, however they increased prices for prospective homeowners.

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

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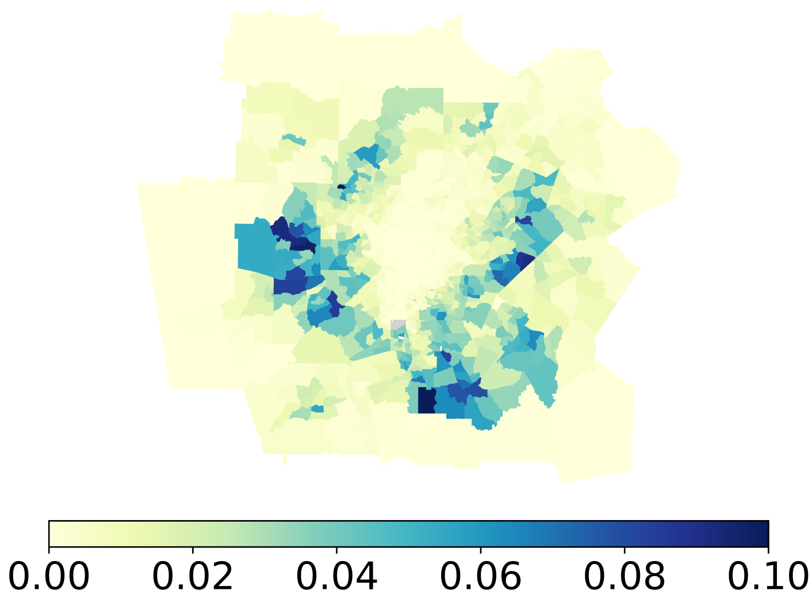
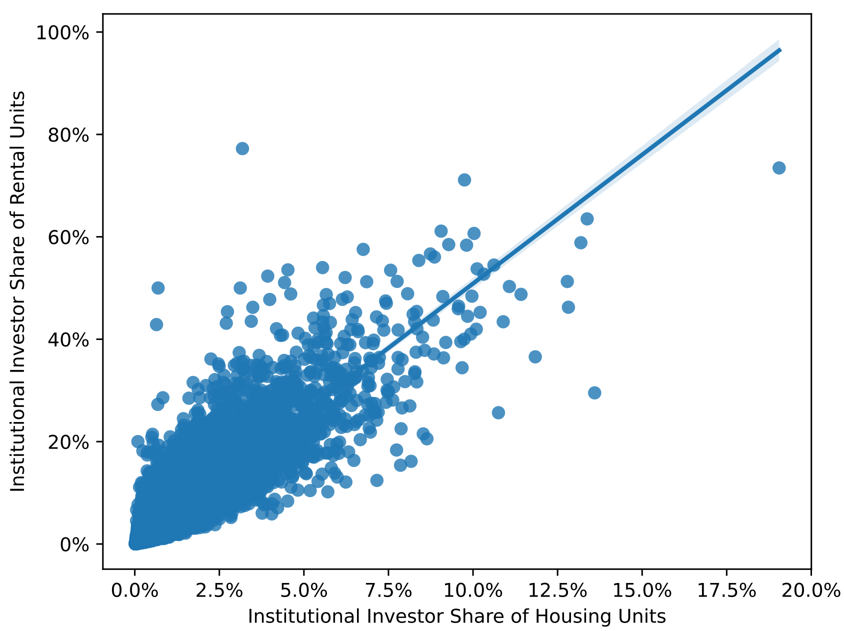
VIII Tables and Figures

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

Panel A: Fraction of housing units owned in Atlanta



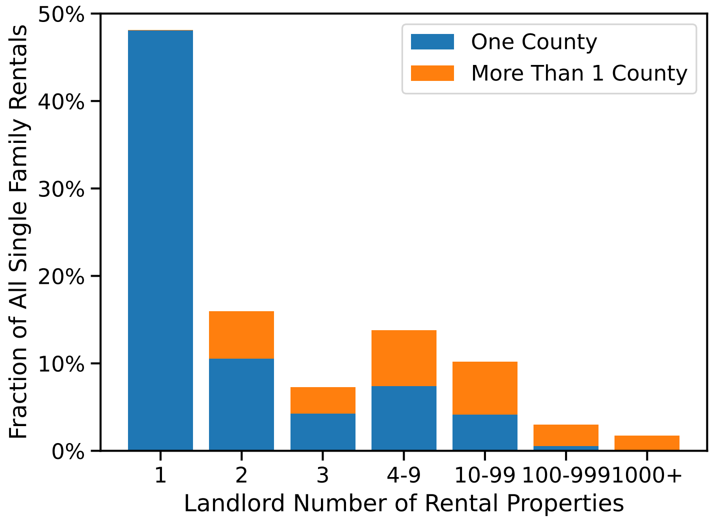
Panel B: Fraction of rentals owned vs housing units owned in the US



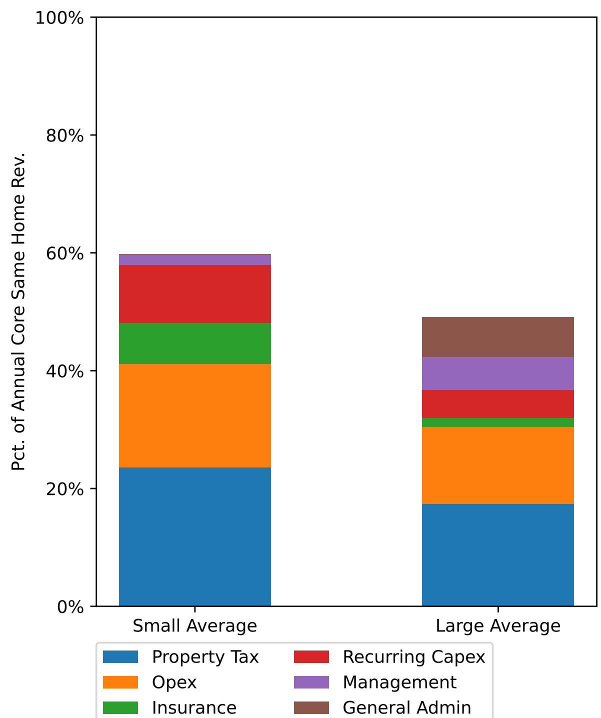
Notes: Panel A shows the fraction of the residential housing stock in a census tract owned by the 7 largest institutional investors in February 2021 in the counties including and surrounding Atlanta, Georgia. The investors included are Invitation Homes, American Homes for Rent, Tricon Residential, FirstKey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

Figure 2: Scale comparison of small and large landlords

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



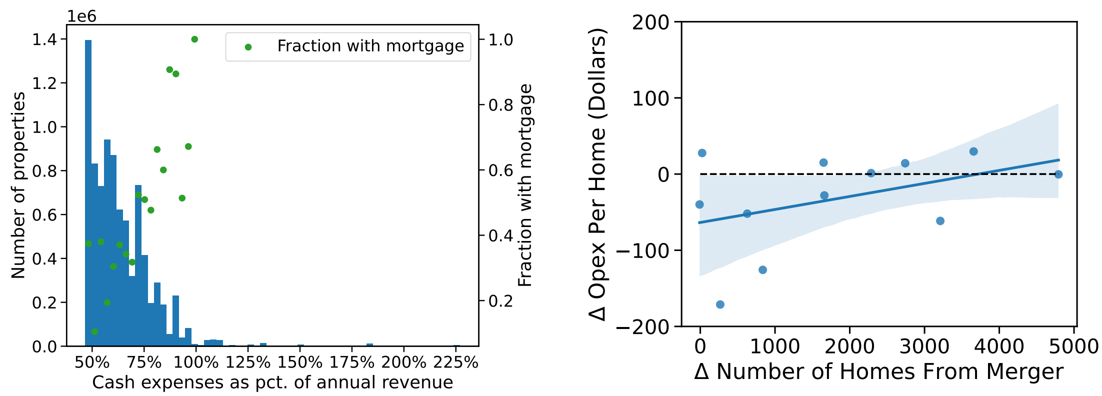
Panel B: Difference between large and small landlord operating costs



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

Figure 3: Scale comparison of small and large landlords

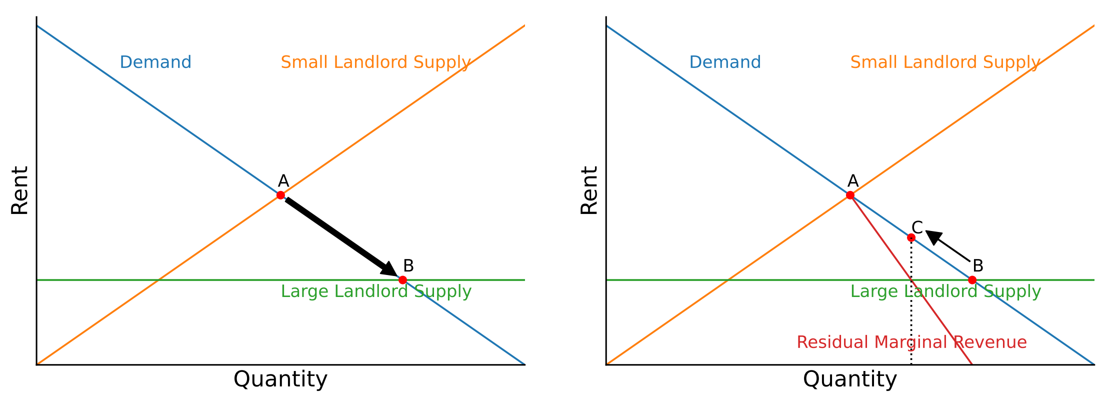
Panel B: Cost heterogeneity for small landlords *Panel A: Change in opex per home from INVH–SWH Merger*



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

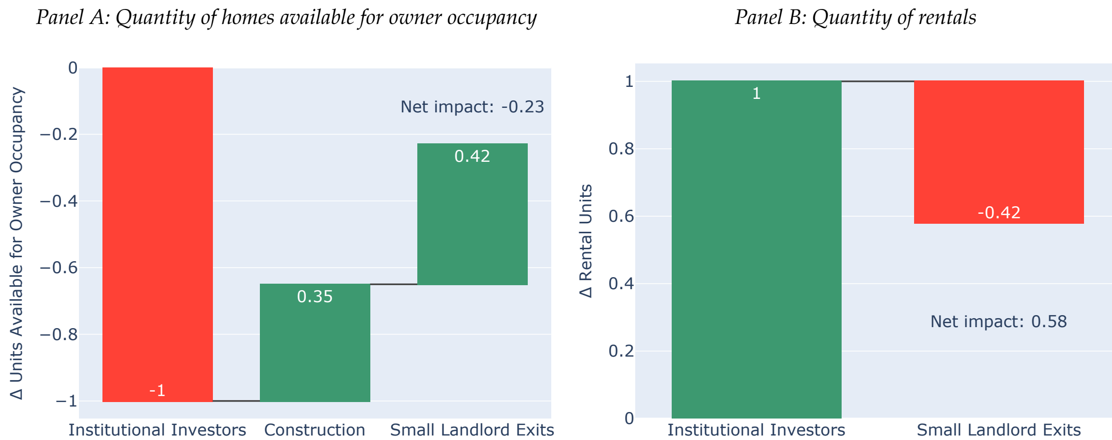
Figure 4: Stylized example of large landlord entry

Panel A: Perfect competition *Panel B: Cournot oligopoly*



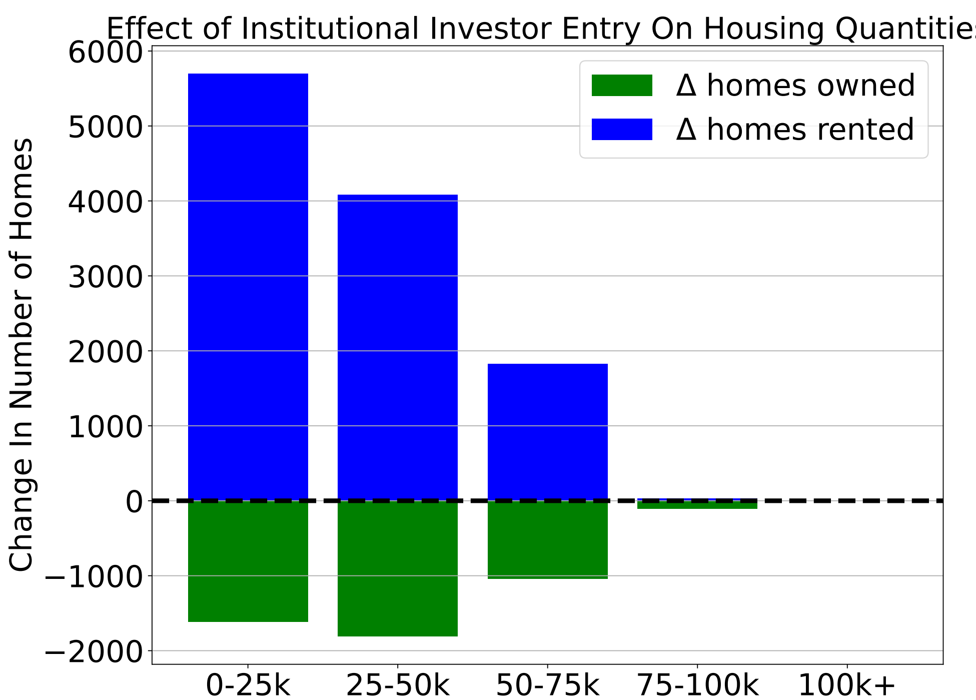
Notes: This figure shows a stylized model of supply and demand for single-family rentals. Households have downward-sloping demand and small landlords have upward-sloping supply. In Panel A, one large landlord with constant returns to scale enters and behaves competitively, which shifts the equilibrium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

Figure 5: Quantity changes upon institutional investors entry



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.

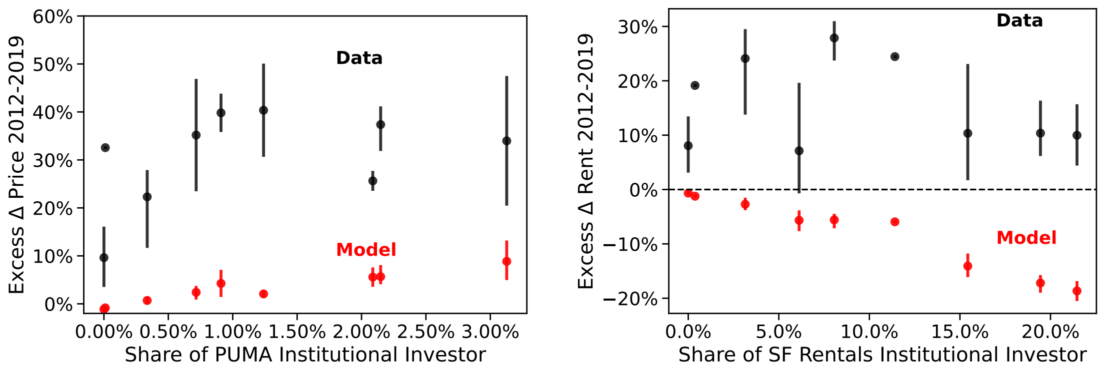
Figure 6: Loss in homes/gains in rentals upon institutional investor entry by income group



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

Figure 7: Price and rent changes upon institutional investors entry

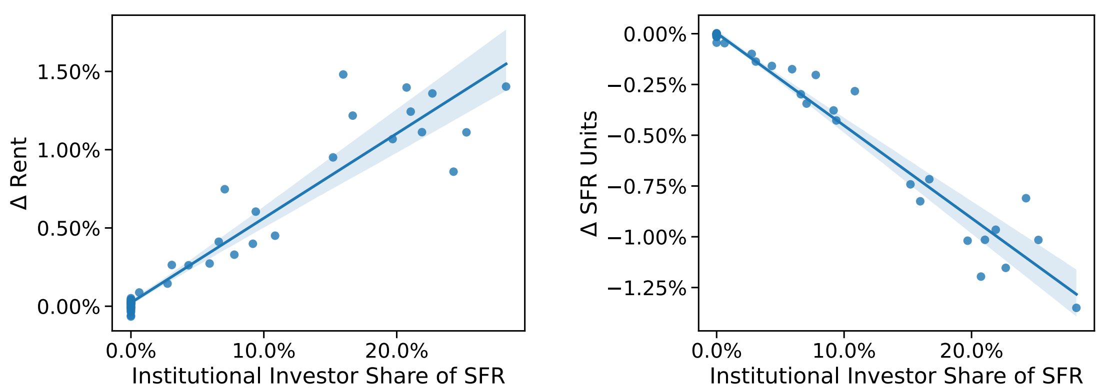
Panel A: Prices *Panel B: Rents*



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

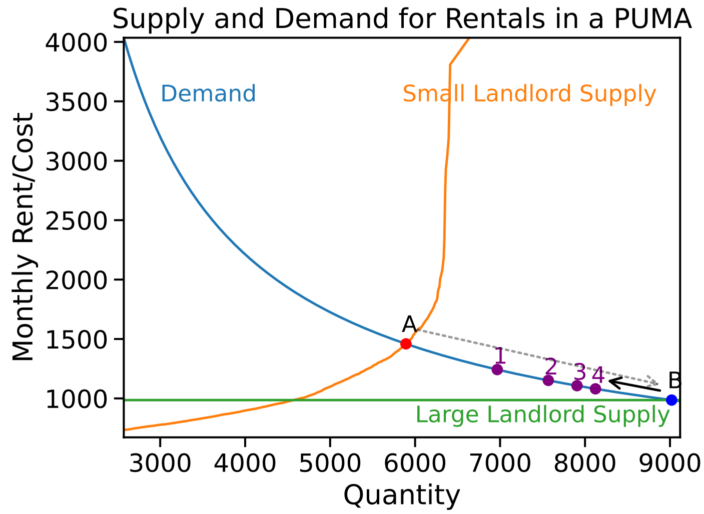
Figure 8: Impact of a merger of large landlords

Panel A: Change in rents *Panel B: Change in quantities*



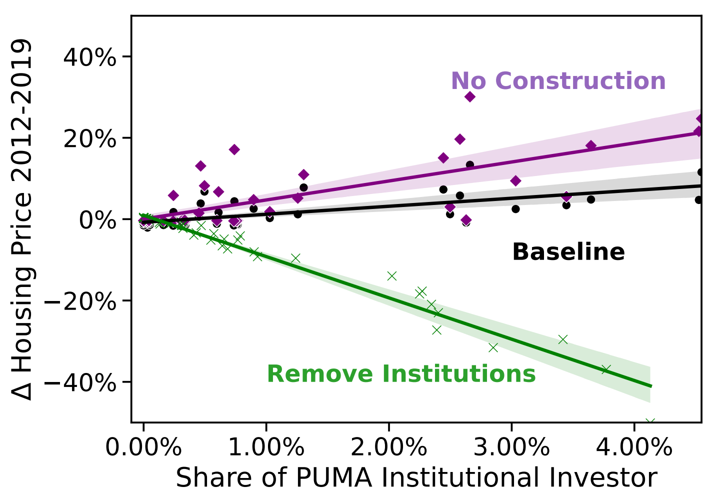
Notes: This figure shows the model-implied impact of a merger of two large landlords, with no adjustment costs. Panel A shows the change in single-family rents due to the merger in each PUMA, and Panel B shows the change in the quantity of single-family rentals in each PUMA. The x axis is the institutional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

Figure 9: Stylized example of merger



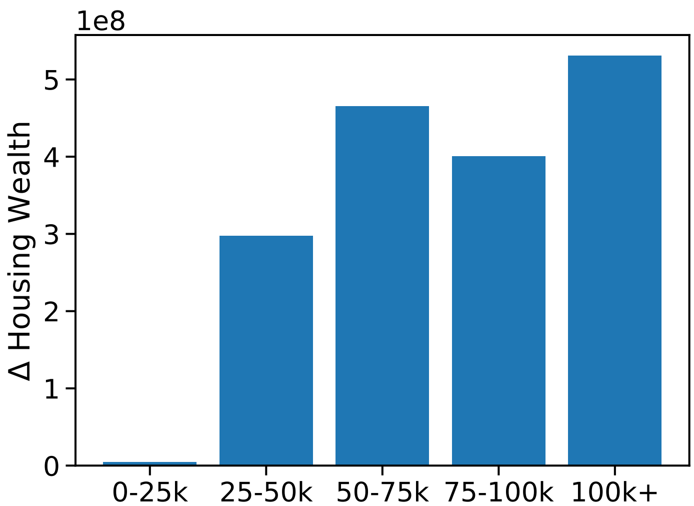
Notes: This figure shows the equilibrium quantities and rents for one PUMA's single-family rental market when there are no large landlords (A), when there are either infinite landlords or the ones that exist choose competitive quantities (B), and then when there are 4, 3, 2, or 1 large landlords. A merger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

Figure 10: Price impact in counterfactual experiments



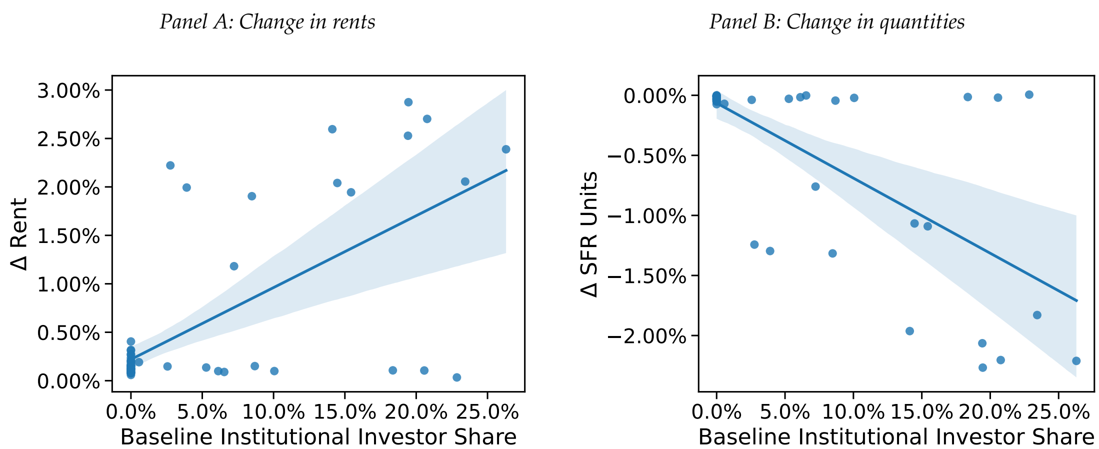
Notes: This figure shows the price impact in each PUMA for the baseline estimation and various counterfactual experiments.

Figure 11: Institutional investor impact on housing wealth



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

Figure 12: Impact of a 5% cap on annual rent increases for large landlords



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

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

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

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

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

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

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

Appendix

A 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. I classify flags of A, T, or null as rentals.

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

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

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

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

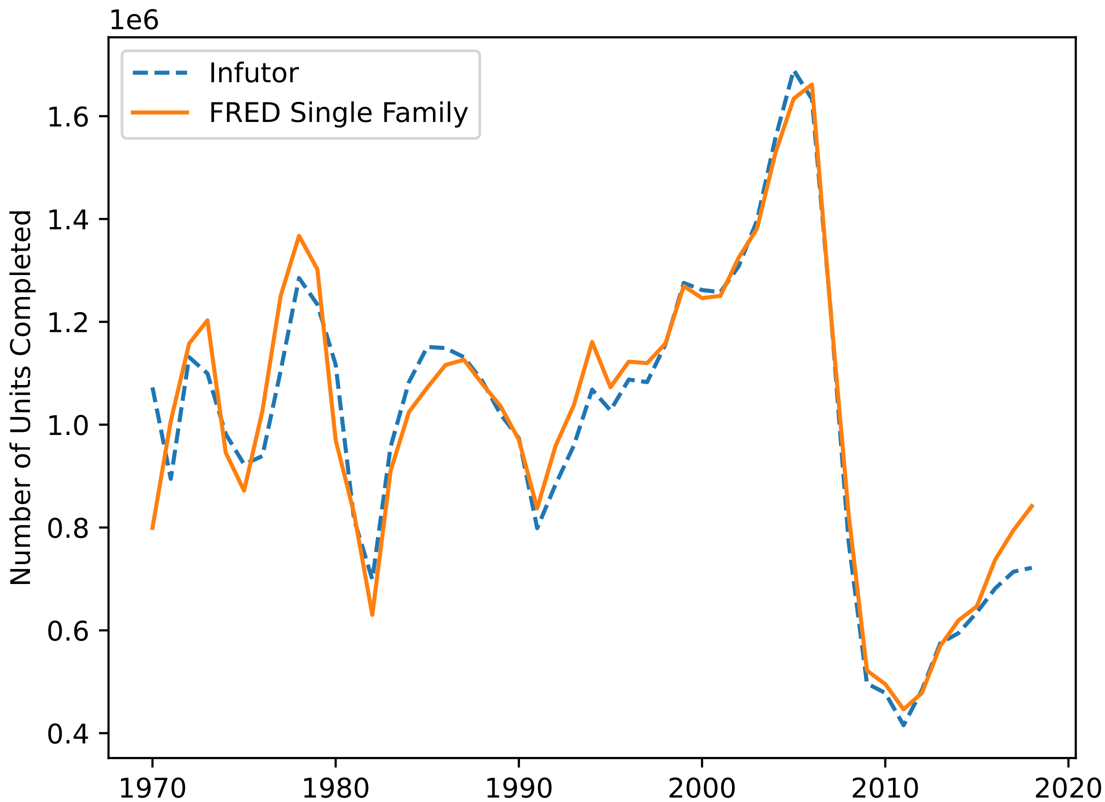
I validate the number of institutional investor–owned homes that I am able to identify for each public company in the table below. The identification is described in the data section of the paper.

Table A2: Verisk number of units compared to public information

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

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

Figure A1: Supply validation



Note: I plot the aggregate number of completions for the US each year from Verisk, where I set the year when a property was built as its completion date. I compare this with aggregate US completions for single-family homes data from Federal Reserve Economic Data (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 with a deceased flag of Y or null

I use an anonymized dataset, so I cannot drop duplicate address histories using names or similar names. Instead, I drop all address histories that are identical. This is possibly an overcorrection, as different people with the same address history would be dropped.

- Reshape from wide to long to obtain the dataset at the person ID$\times$address$\times$ previous address level, with the date recorded at the previous address and date recorded at the current address

- Drop those with null ZIP codes, true duplicates, and duplicates

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

- Of the duplicates at the PID$\times$ EFFDATE level, drop those that do not merge to a property identifier from the cleaned property dataframe

- Of the remaining duplicates, 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. Keep the duplicate that has the first rank in that order.

- Drop all entries that have remaining duplicates and do not select one of the duplicates to keep

From these cleaned data, I create two types of datasets. One is the sum of all moves between census PUMAs and asset classes (owner occupied, single-family rental, and multi-family rental) from 2012 to 2019. I use this dataset for the estimation of migration costs. The other dataset examines moves in a given year to see where people who move into institutional investor homes come from. I create a window such that those who moved before the start of the window are considered residents of their most recent location and those who moved during the window are considered movers from their previous location to their new one. Those who move after the window are not considered movers.

- 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 a ZIP code

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

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

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

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

Note: *p<0.1; **p<0.05; ***p<0.01. This table regresses Verisk county-to-county moves on Census county-to-county moves.

A.3 Small Landlord Costs

To construct a dataset of small landlords' single-family rental cost components, I start with the RHFS's publicly available data for 2018 and 2021. I filter the dataset as follows:

- Keep only 1-unit properties
- Keep only "individual" type owners, which excludes corporations, REITs, and LLCs

- For 2021, exclude townhouses (for 2018, this field does not exist)
- Exclude assisted living homes and rent control homes
- Keep only homes with lease lengths of 1 year
- Keep homes with rent and market value both greater than 0

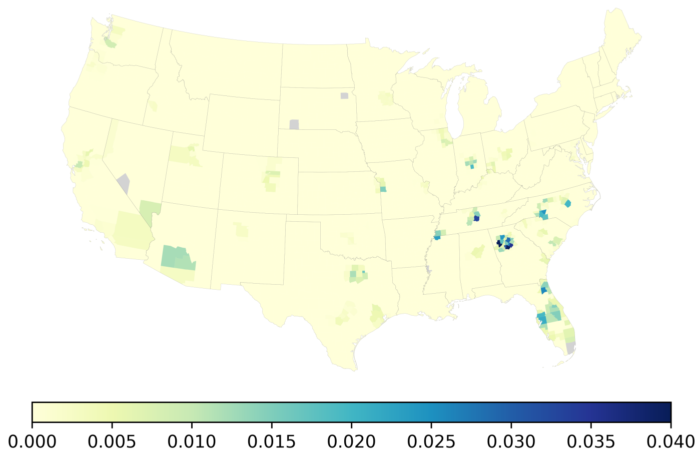
This results in a dataset of 601 individual landlords of 1-unit properties.

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

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

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 owned at the county level. These 7 are Invitation Homes, American Homes for Rent, Tricon Residential (now owned by Blackstone), Progress Residential, FirstKey Homes, Main Street Renewal, and Home Partners of America.

Table B1: Institutional investor market presence

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

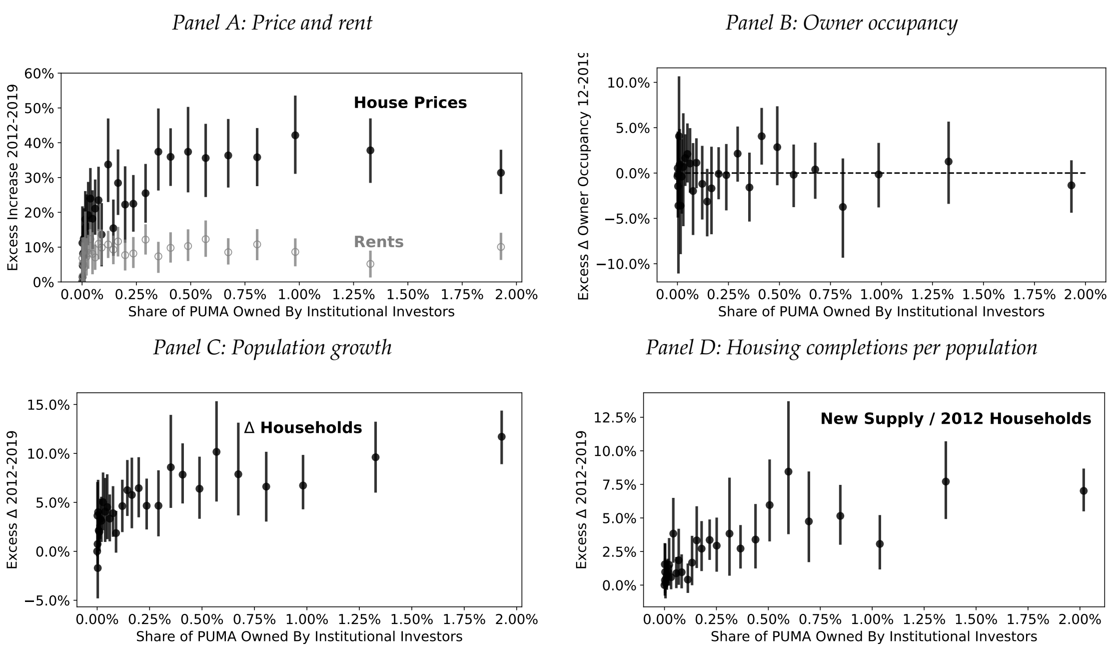
Note: *p<0.1; **p<0.05; ***p<0.01. This is a descriptive regression at the PUMA level. The dependent variable is an indicator variable for PUMAs in which the institutional investors, combined, have 10 or more properties in the PUMA. Column 1 has no fixed effects, and column 2 has state-level fixed effects.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

Table B2: Within-ZIP-code differences in housing characteristics

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

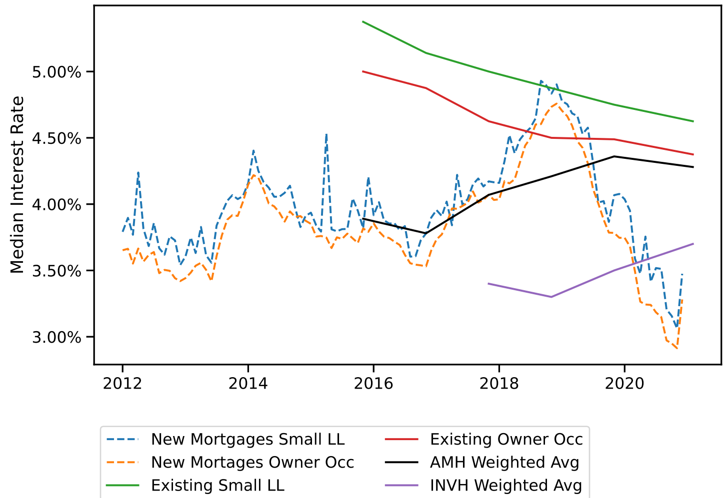
Note: From Verisk property data, I identify institutional investor holdings and compare their physical features in a given ZIP code with the features of the rest of the rental stock and of owner-occupied homes. I take these within-ZIP-code differences and compute a weighted average, weighted by the number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

Figure B2: Associations with institutional investor share of housing stock



Notes: This figure shows 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 for the variable relative to the value for the rest of the country. Panel A is the change in the fraction of homes owner-occupied from 2012 to 2019 from the American Community Survey 1-year (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 the fraction owner-occupied from 2012 to 2019 from the ACS1. Panel C is the change in the number of households from 2012 to 2019. Panel D is the amount of new construction from 2012 to 2019 divided by the number of households present in 2012. The new construction counts come from the Verisk property files.

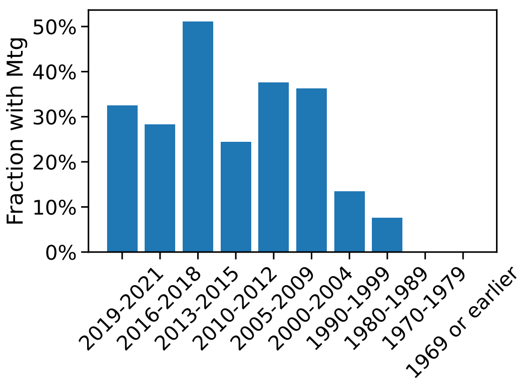
Figure B3: Cost of debt



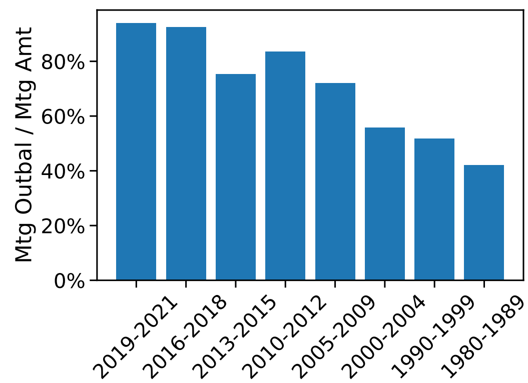
Note: This figure shows median interest rates for new mortgages for small landlords, new mortgages for owner-occupied homes, all existing mortgages for small landlords, all existing mortgages for owner-occupants, American Homes for Rent's debt, and Invitation Homes' debt. Data for the small landlords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

Figure B4: Small landlord mortgages

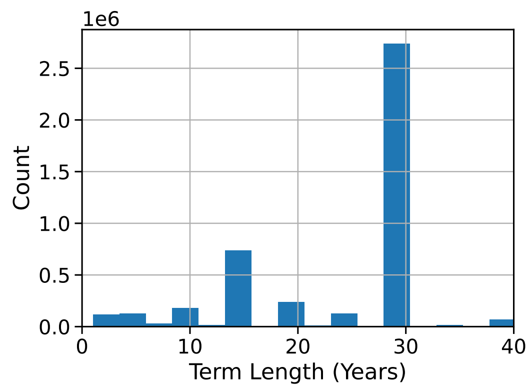
Panel A: Fraction of small landlords with mortgage by purchase date



Panel B: Mortgage % remaining

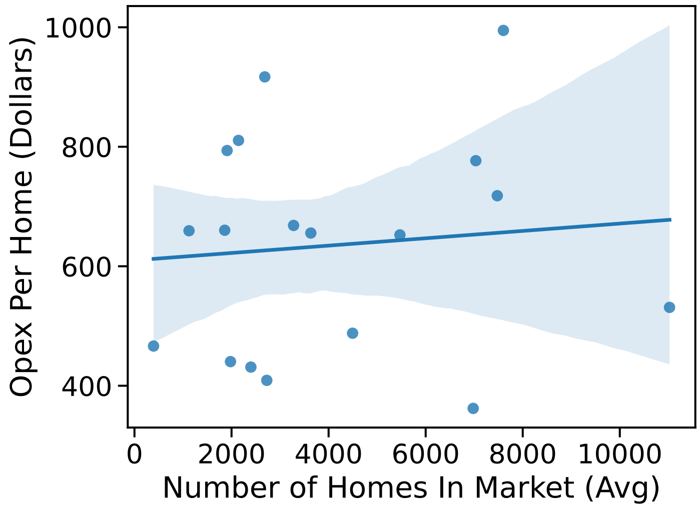


Panel C: Small landlord term length distribution



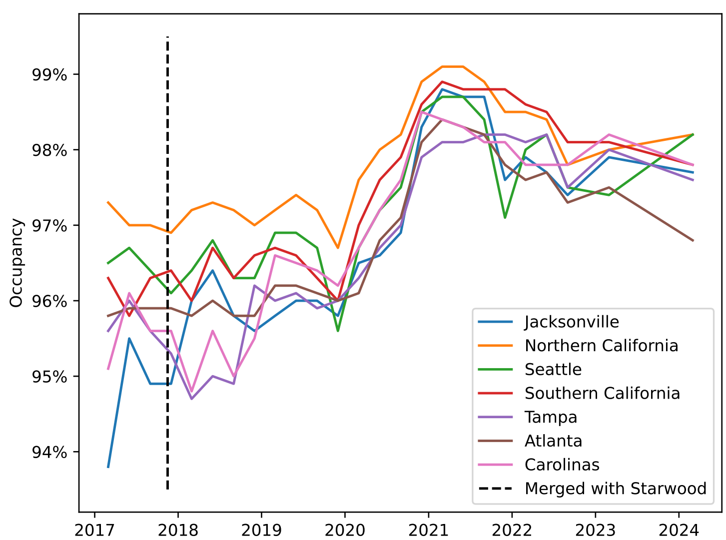
Notes: Panel A shows the fraction of small landlords in a bucket who have a mortgage in the 2021 sample of the Rental Housing Finance Survey, where each bucket is a purchase date grouping. Panel B shows the fraction of the original mortgage balance remaining for each purchase year bucket for those who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

Figure B5: INVH market average opex per home



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

Figure B6: Market-level occupancy rates for Invitation Homes



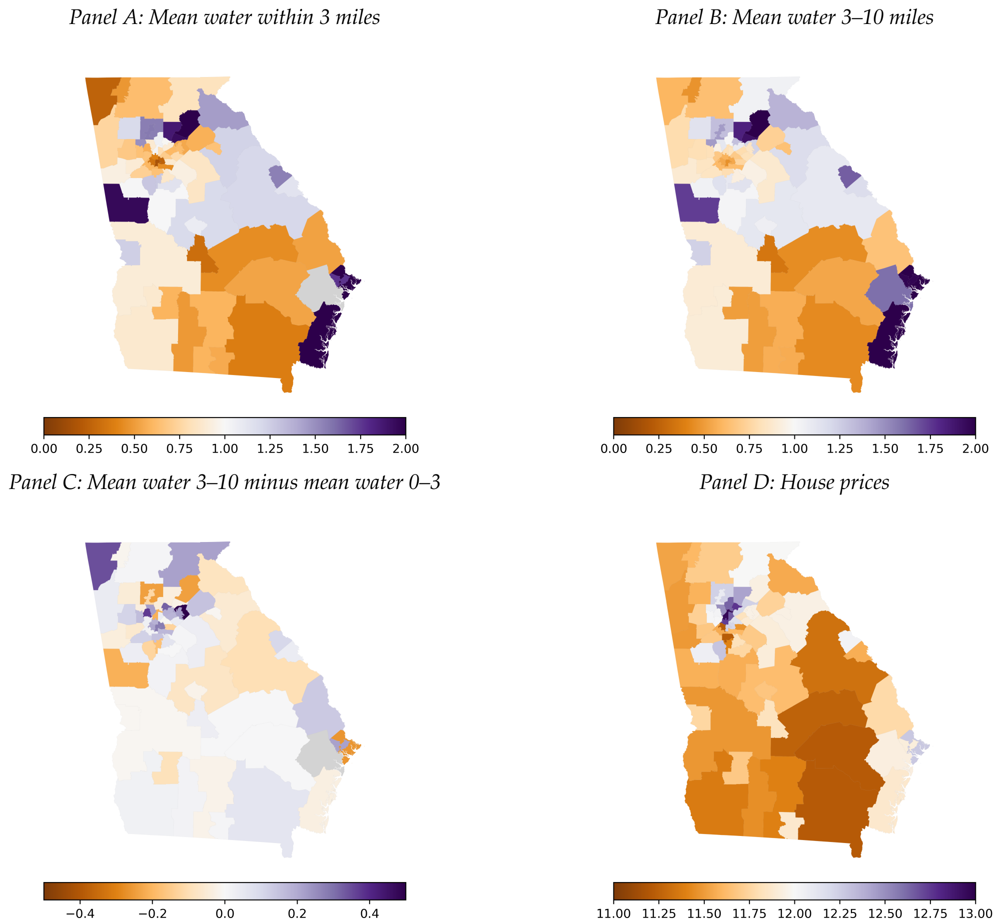
Note: This figure shows the market-level occupancy for Invitation Homes for a number of its markets. The dotted black line is the date when Invitation Homes merged with Starwood Waypoint Homes and gained 32,000 homes.

Table B3: First stage for household demand

	log(Price)	log(Rent)
log(Land Unavail 0–3 mi)	0.0028	-0.0166***
log(Land Unavail 3–10 mi)	0.0647***	0.0169***
log(Wetlands 0–3 mi)	0.0020	-0.0089
log(Wetlands 3–10 mi)	-0.0130	0.0399***
log(Water 0–3 mi)	-0.0480***	-0.0520***
log(Water 3–10 mi)	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 FE	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 results of a pooled instrumental variables regression of indirect utilities on characteristics for the whole US from 2012 to 2019. Topography characteristics are described for both the area within 3 miles of the average census tract within a PUMA and the area within a 3–10 mile ring from that census tract. These features are total land unavailability, amount of water, and amount of wetlands, all from Lutz and Sand (2022). Other characteristics shown are the median number of rooms, median year built of housing, and fraction of a PUMA's housing stock that is single-family. These three characteristics are also included for neighboring PUMAs. Instruments are the characteristics for the 3–10 mile rings and the neighboring PUMAs. They are ordered next to the results for the within-3-mile circle for comparison. Partial F statistics for the instruments are reported below.

Figure B7: Examining the instrument



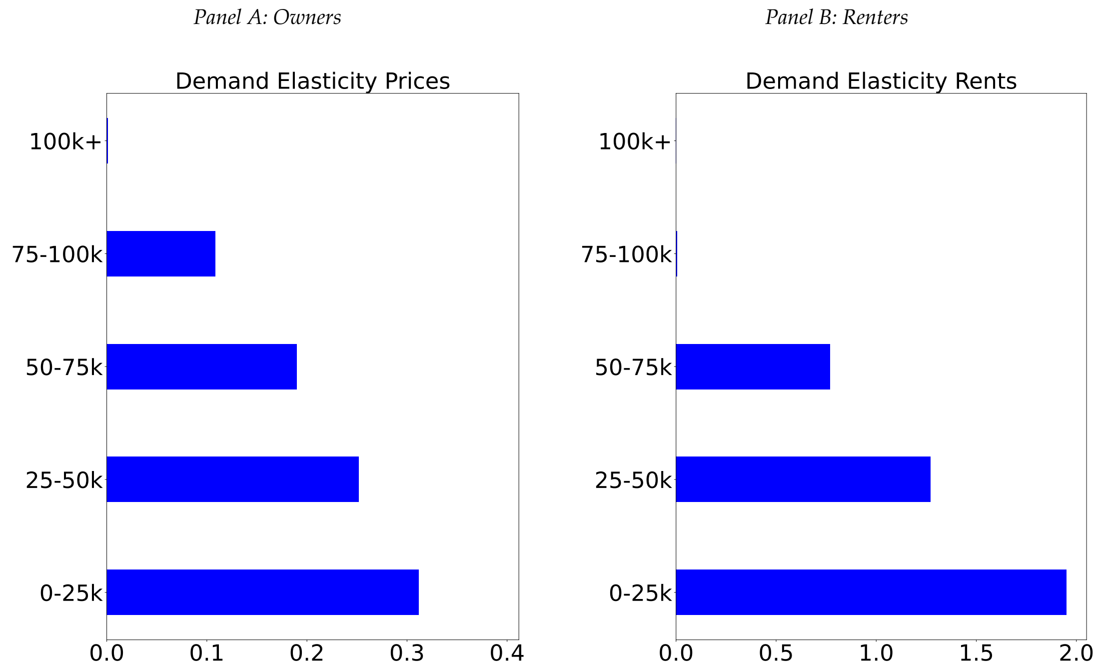
Note: This figure shows some characteristics of topography and prices for Georgia. Panel A shows the mean amount of water within 3 miles of each census tract in a PUMA. Panel B shows the same figure for the 3–10 mile ring around the census tract. Panel C shows the average difference between the mean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

Table B4: 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's residents who move from origin i to destination j divided by the share moving to the outside asset. The outside asset is defined as all PUMAs missing data on a nonprice characteristic, with housing prices below \$80k or with rent below \$500. This is a pooled regression using bilateral migration data from 2012 to 2019 from Verisk.

Figure B8: Demand elasticities



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

Table B5: Household estimation for rental housing

Parameter	0-25k	25-50k	50-75k	75-100k	100k+
Log(Rent)	-1.952***	-1.276***	-0.766***	-0.003	-0.001
	[-2.18, -1.73]	[-1.49, -1.06]	[-0.99, -0.54]	[-0.29, 0.29]	
Med. Year Built	0.000	0.001***	0.001***	0.001**	0.001***
	[-0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]
Med. Number of Rooms	-0.118***	-0.096***	-0.148***	-0.193***	-0.549***
	[-0.17, -0.06]	[-0.14, -0.05]	[-0.2, -0.09]	[-0.26, -0.12]	[-0.6, -0.5]
Frac. Single Family Rentals	-0.811***	-0.527***	-0.355***	-0.388***	-0.192**
	[-0.95, -0.67]	[-0.66, -0.39]	[-0.51, -0.2]	[-0.57, -0.2]	[-0.36, -0.02]
Frac. Less 45 Min Commute	-0.032	0.594***	0.956***	1.148***	0.149
	[-0.27, 0.21]	[0.37, 0.82]	[0.7, 1.22]	[0.83, 1.47]	[-0.06, 0.36]
Frac. High School Enrollment	-0.265	0.132	0.469**	0.809***	2.308***
	[-0.62, 0.09]	[-0.21, 0.48]	[0.09, 0.84]	[0.27, 1.34]	[1.82, 2.79]
Frac. High School Private	0.093	-0.276**	-0.147	0.155	1.302***
	[-0.15, 0.33]	[-0.51, -0.04]	[-0.4, 0.11]	[-0.14, 0.45]	[1.1, 1.51]
Log(Distance All)	-0.118***	-0.051***	-0.029***	-0.047***	-0.037***
	[-0.14, -0.1]	[-0.07, -0.04]	[-0.05, -0.01]	[-0.07, -0.02]	[-0.06, -0.01]
Log(Distance Top 30)	-0.042***	-0.062***	-0.091***	-0.107***	-0.194***
	[-0.06, -0.02]	[-0.08, -0.04]	[-0.11, -0.07]	[-0.14, -0.08]	[-0.21, -0.18]
Jan. Temp.	0.018***	0.014***	0.014***	0.013***	0.016***
	[0.02, 0.02]	[0.01, 0.02]	[0.01, 0.02]	[0.01, 0.02]	[0.01, 0.02]
Jan. Sunlight	0.003***	0.002***	0.002***	0.001***	0.002***
	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]
July Temp.	-0.033***	-0.022***	-0.020***	-0.020***	-0.025***
	[-0.04, -0.03]	[-0.03, -0.02]	[-0.02, -0.02]	[-0.03, -0.01]	[-0.03, -0.02]
July Humidity	-0.001**	-0.002***	-0.002***	-0.002**	-0.003***
	[-0.0, -0.0]	[-0.0, -0.0]	[-0.0, -0.0]	[-0.0, -0.0]	[-0.0, -0.0]
log(Land Unavail 3mi)	-0.048***	-0.071***	-0.065***	-0.080***	-0.059***
	[-0.06, -0.04]	[-0.08, -0.06]	[-0.08, -0.05]	[-0.1, -0.06]	[-0.08, -0.04]
log(Wetlands 3mi)	-0.018**	-0.002	-0.004	-0.001	0.029***
	[-0.03, -0.0]	[-0.01, 0.01]	[-0.02, 0.01]	[-0.02, 0.02]	[0.01, 0.05]
log(Water 3mi)	0.056***	0.045***	0.034***	0.036***	0.057***
	[0.04, 0.07]	[0.03, 0.06]	[0.02, 0.05]	[0.01, 0.06]	[0.04, 0.08]
Single Family Rental	-1.046***	-0.908***	-0.798***	-0.676***	-0.260***
	[-1.11, -0.98]	[-0.97, -0.84]	[-0.87, -0.73]	[-0.77, -0.59]	[-0.29, -0.23]

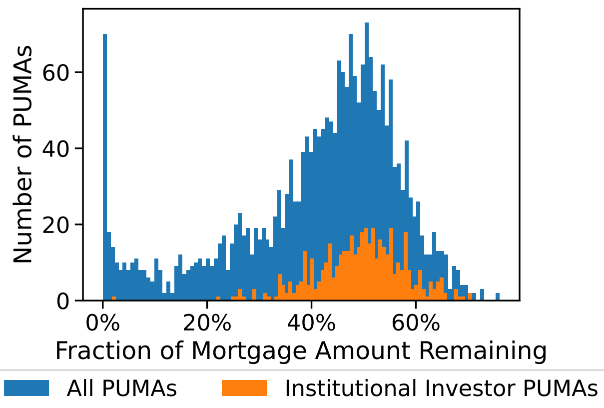
Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the results of the estimation for Equation (21) for the coefficients related to rental housing. It includes year fixed effects which are not shown in this table. Coefficients are the log of the PUMA level rent, the median year built and median number of rooms of rental housing in the PUMA, the fraction of the PUMA that is single-family housing, the fraction of households in the PUMA who have less than a 45 minute commute, the fraction of high school aged population in the PUMA who are enrolled in high school, the fraction of the same group enrolled in private school, the log of the distance to the nearest MSA, the log of the distance to the nearest top 30 MSA, weather controls, topography controls from Lutz and Sand (2022), and whether the rentals they live in are single-family rentals or not. Rents are different in the estimation for single-family rentals and multifamily rentals. Elasticity with respect to rent is constrained to be -0.001 for highest income group.

Table B6: Household estimation for owner occupied housing

Parameter	0-25k	25-50k	50-75k	75-100k	100k+
Log(Price)	-0.412***	-0.359***	-0.291***	-0.201***	-0.001
	[-0.47, -0.35]	[-0.41, -0.31]	[-0.34, -0.24]	[-0.25, -0.15]	
Med. Year Built	-0.000	0.000**	0.000***	0.001*	0.000***
	[-0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[-0.0, 0.0]	[0.0, 0.0]
Med. Number of Rooms	-0.026*	-0.031**	-0.044***	-0.058***	-0.158***
	[-0.05, 0.0]	[-0.05, -0.01]	[-0.07, -0.02]	[-0.08, -0.03]	[-0.17, -0.14]
Frac. Single Family Rentals	0.064*	0.309***	0.406***	0.492***	0.693***
	[-0.0, 0.13]	[0.24, 0.38]	[0.35, 0.46]	[0.44, 0.55]	[0.64, 0.75]
Frac. Less 45 Min Commute	-0.246***	-0.123**	-0.139**	-0.174***	-0.256***
	[-0.37, -0.12]	[-0.23, -0.01]	[-0.24, -0.03]	[-0.29, -0.06]	[-0.33, -0.18]
Frac. High School Enrollment	-0.358***	-0.175**	-0.026	0.139*	0.650***
	[-0.53, -0.18]	[-0.34, -0.01]	[-0.18, 0.12]	[-0.02, 0.29]	[0.51, 0.79]
Frac. High School Private	0.399***	0.297***	0.296***	0.301***	0.673***
	[0.29, 0.51]	[0.2, 0.39]	[0.2, 0.39]	[0.21, 0.4]	[0.6, 0.75]
Log(Distance All)	0.016***	0.020***	0.020***	0.023***	0.033***
	[0.01, 0.03]	[0.01, 0.03]	[0.01, 0.03]	[0.01, 0.03]	[0.02, 0.04]
Log(Distance Top 30)	0.012***	-0.013***	-0.030***	-0.041***	-0.069***
	[0.0, 0.02]	[-0.02, -0.01]	[-0.04, -0.02]	[-0.05, -0.03]	[-0.07, -0.06]
Jan. Temp.	0.003***	0.001	-0.000	-0.002***	-0.002***
	[0.0, 0.0]	[-0.0, 0.0]	[-0.0, 0.0]	[-0.0, -0.0]	[-0.0, -0.0]
Jan. Sunlight	0.002***	0.001***	0.001***	0.001***	0.001***
	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]
July Temp.	-0.006***	-0.004***	-0.003***	-0.002*	0.004***
	[-0.01, -0.0]	[-0.01, -0.0]	[-0.01, -0.0]	[-0.0, 0.0]	[0.0, 0.01]
July Humidity	0.001***	0.001***	0.001***	0.001***	0.002***
	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]
log(Land Unavail 3mi)	0.059***	0.029***	0.014***	0.004	0.001
	[0.05, 0.07]	[0.02, 0.04]	[0.01, 0.02]	[-0.0, 0.01]	[-0.01, 0.01]
log(Wetlands 3mi)	-0.018***	-0.009***	-0.005	-0.001	0.002
	[-0.02, -0.01]	[-0.01, -0.0]	[-0.01, 0.0]	[-0.01, 0.0]	[-0.0, 0.01]
log(Water 3mi)	0.013***	0.011***	0.009**	0.006	0.002
	[0.0, 0.02]	[0.0, 0.02]	[0.0, 0.02]	[-0.0, 0.01]	[-0.01, 0.01]

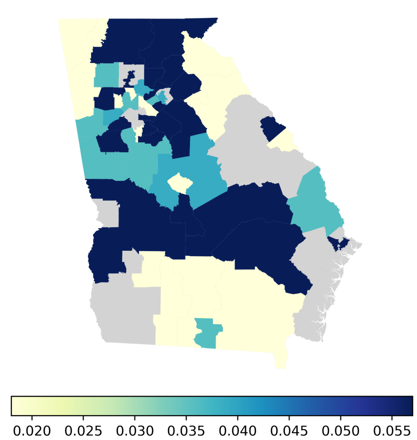
Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the results of the estimation for Equation (21) for the coefficients related to owner occupied housing. It includes year fixed effects which are not shown in this table. Coefficients are the log of the PUMA level purchase price of housing, the median year built and median number of rooms of owner occupied housing in the PUMA, the fraction of the PUMA that is single-family housing, the fraction of households in the PUMA who have less than a 45 minute commute, the fraction of high school aged population in the PUMA who are enrolled in high school, the fraction of the same group enrolled in private school, the log of the distance to the nearest MSA, the log of the distance to the nearest top 30 MSA, weather controls, and topography controls from Lutz and Sand (2022). Elasticity with respect to rent is constrained to be -0.001 for highest income group.

Figure B9: PUMA-level average fraction of mortgage amount remaining for small landlords



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

Figure B10: Expected rent growth



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

Table B7: 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 with actual 2012 rents and prices for the small landlord estimation. I compare the estimated PUMA quantities to the actual quantities in 2012 for all of Georgia and for PUMAs where institutional investors have 1000 or more units, which I call high-investor-activity regions. I first report the correlations between the estimated quantities and the actual quantities. Then, I report the median of the estimated quantity divided by the actual quantity. Next, I raise rents by 1%, measure the change in quantity in each region and report the median change as the median elasticity with respect to rent. Finally, I raise prices by 1%, measure the change in quantity in each region and report the median as the median elasticity with respect to price.

Table B8: Small landlord fitted elasticities

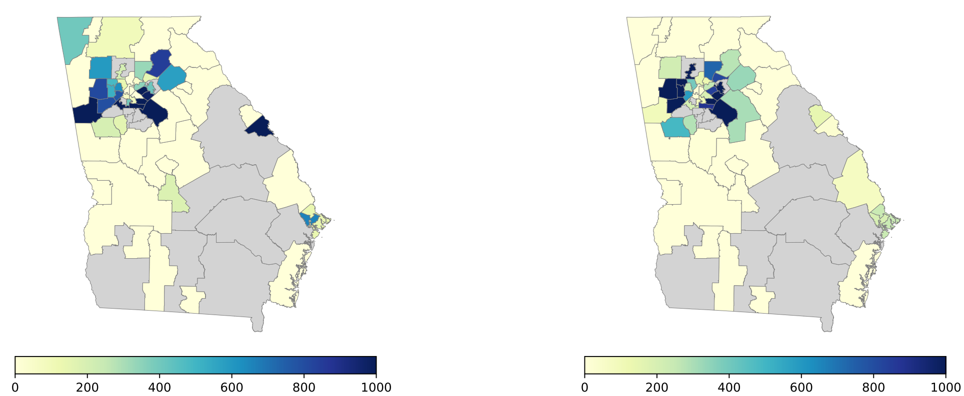
	Dependent variable: Elasticity with respect to price
	Georgia
	(1)
Intercept	14.15***
	(2.59)
Expected Rent Growth Pct	0.33***
	(0.08)
Log(Price/Rent)	-2.83***
	(0.47)
Mean Mortgage Balance Pct	-2.00**
	(0.87)
Property Tax Rate Pct	-0.14
	(0.49)
Observations	57
R^2	0.55

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 B11: Large landlord estimation fit

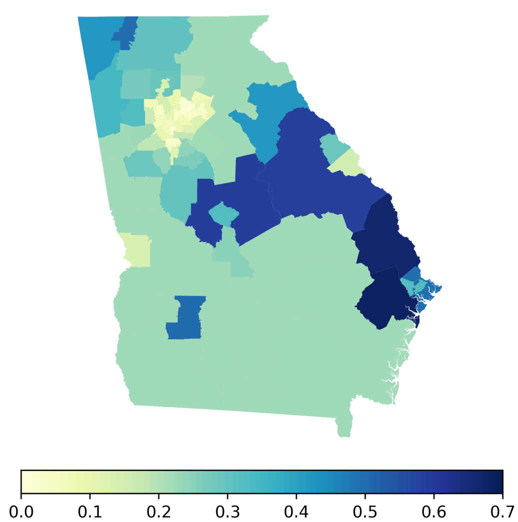
Panel A: Estimated large landlord quantities

Panel B: Actual quantities



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

Figure B12: Supply elasticities for Georgia



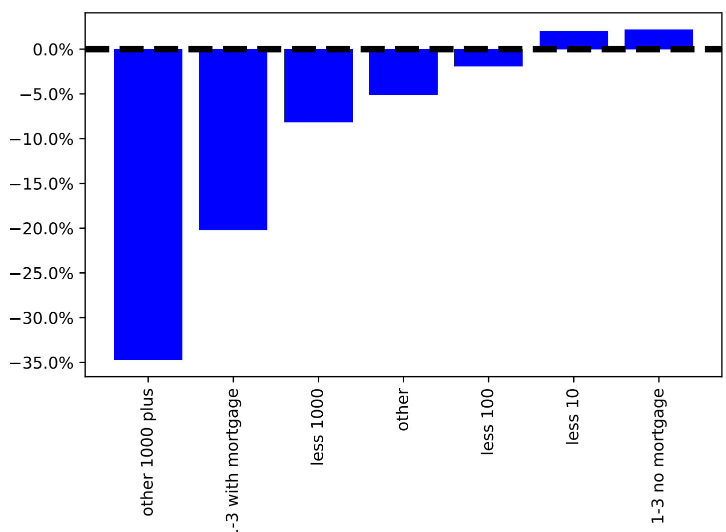
Note: This figure shows the new unit supply elasticities for Georgia, aggregated from the census tract–level elasticities from Baum-Snow and Han (2024). Missing PUMA elasticities are imputed with the state-level mean, which here is 0.22.

Table B9: Association of landlord exits with institutional investor entry

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

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

Figure B13: Association of landlord exits by landlord type



Note: This chart shoes the coefficients from regressions of the change in a specific landlord type's holdings at the census tract level on the change in institutional landlord holdings from 2016–2021 with county fixed effects. The regression is run for landlords with more than 1000 homes who are not classified as institutional investors who buy homes to rent, landlords with 1-3 homes who have mortgage data, landlords with 101-999 homes, other types of landlords including flippers and investment companies, landlords with 11-99 homes (less .

C Calculating Counterfactual Home Prices

To compute counterfactual market-clearing prices, I use the Newton's method algorithm 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:

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

Again 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 on 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, supply is upward sloping, and there is no issue with convergence to a stable equilibrium in my simulations.