The Expansion and Dynamic Equilibrium Effects of Institutional Landlords*

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Abstract

This paper studies how dynamically formed cost efficiencies from scope and density drive institutional landlords' expansion and, in turn, alter the distribution of welfare across heterogeneous households in single-family housing markets. Institutional landlords convert owner-occupied homes into large, spatially clustered rental portfolios. They constrain households' access to homeownership while expanding rental opportunities. This leads households to reoptimize between buying and renting, as buyers may face higher prices while renters may benefit from expanded choice sets. We build a dynamic equilibrium model of landlord investment with three key features: (i) oligopolistic landlords' investment determines the evolution of housing supply structure, (ii) portfolio size and density introduce endogenous variation in landlord costs, and (iii) households substitute within and across buying and renting in an integrated choice set. We estimate the model using firm-property-level data from 2013 to 2022 in the Atlanta metropolitan area. We find that institutional landlords' expansion achieved a 60.03% reduction in maintenance cost from economies of scope and density. Households' total welfare increased, with varying effects across renters and buyers. The majority of renters gained from expanded rental supply, while a small fraction of renters, together with most buyers, lost from diminished access to affordable homeownership. Our findings have significant policy implications for regulating institutional landlords' expansion in the single-family home market.

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1 Introduction

The rise of institutional landlords over the past decade has reallocated housing supply in the single-family home market across Sun Belt metro areas. These firms convert owner-occupied homes into large, spatially clustered rental portfolios. Critics argue that their expansion exacerbates the housing affordability crisis by bidding up homeownership prices and constraining households' access to affordable homeownership. Proponents counter that institutional landlords expand rental supply with standardized products, achieving potential cost efficiencies compared to local small landlords. In this paper, we ask how dynamically formed cost efficiencies from scope and density drive institutional landlords' expansion in competition and, in turn, alter welfare distribution across heterogeneous households.

To answer this question, we analyze linked datasets of property transactions, rental listings, resident demographics, and institutional ownership in the Atlanta metropolitan area. We document three key patterns in institutional landlords' expansion. First, institutional landlords have expanded rapidly by actively acquiring single-family homes and converting them into rentals. From 2013 to 2022, the top six institutional landlords acquired over 50,000 single-family homes, or 3% of the total housing stock. Second, these landlords tend to form spatially clustered portfolios, with location priorities differentiated from competitors. By 2022, 65.8% of their rental units were located in areas with more than 25 units within a one-mile radius managed by the same landlord. Third, institutional landlords target their acquisitions toward lower-priced segments, with purchase activity peaking among the 20th–30th percentiles of sale prices among all homes for sale. Finally, we find correlational effects of institutional landlords' expansion on the local housing market. In the ownership segment, their expansion correlates with higher sale prices, increased transaction volumes, and a reduction in individual home purchases. In the rental segment, their investment coincides with expanded total rental supply, with no clear price effects.[1]

Motivated by these patterns, we develop a dynamic equilibrium model of landlord investment with embedded static housing market equilibrium in each period. The model highlights (i) endogenous housing supply evolution determined by oligopolistic landlords' investment, (ii) endogenous landlord costs varying with portfolio size and density, and (iii) households' substitution within and across buying and renting in an integrated choice set. Furthermore, the static equilibrium incorporates rich heterogeneity in housing demand, which facilitates the analysis of welfare impacts across household demographics.

Institutional landlords are dynamic investors, adjusting their rental portfolios each period by choosing how many and which types of homes to buy or sell. Conditional on landlord investment, housing prices are determined via market clearing in a vacancy-free equilibrium. Unlike small

[1] We find very small (in scale) yet statistically significant negative effects on rental prices for properties run by local small landlords, and a very small (in scale) yet statistically significant gap in rental prices between small landlords' properties (lower) and institutional landlords' properties (higher).

landlords, each institutional landlord faces endogenous per-unit cost of maintenance that vary with portfolio size and local density. The optimal pace of investment balances an intertemporal trade-off between rising acquisition costs today and expected profit increases in the future. Given locally constrained housing inventories, rapid densification of firms' property networks drives up home prices, an effect that is more prominent when multiple firms compete in acquisition in the same location. To mitigate these congestion costs, optimal investment path features spreading smaller-scale investments over multiple periods and spatially differentiating from competitors.

In the static housing equilibrium, institutional landlords' investment constitutes a fraction of demand for ownership and updates their rental supply. We micro-found households' housing demand using a heterogeneous-coefficient nested logit model. To capture all types of households' substitutions within and across buying and renting as institutional landlords expand, we assume a unified housing choice set containing all tenure types. Households choose among options in three nests: homes for sale, homes for rent, and non single-family home outside options. Small landlords are price-taking atomistic agents making binary entry-exit decisions, which aggregate into their demand and supply of ownership and their updated rental supply. Given prices, incumbent homeowners make selling decisions, which aggregate into their supply of ownership. The static equilibrium is solved by ownership and rental prices that jointly clear the ownership and rental segments.

We estimate the model using data on institutional landlords' investment, household housing choices, and incumbent supply decisions in Atlanta single-family home market from 2013-2021. Parameters of interest include housing demand, homeownership supply, small-landlord rental supply, and institutional landlords' investment costs and maintenance costs. Estimation proceeds in two steps. First, we recover the static demand parameters using Generalized Method of Moments (GMM) estimator, leveraging the exogenous part of cross-market variations in housing supply structure as an instrument for housing prices and to identify the nesting parameter. We leverage cross-market variation in housing population demographics to instrument for endogenous prices in the homeownership supply and small landlord rental supply, to identify static supply parameters. In the second step, we follow the two-step estimation framework and adapt it to the multi-product firms' continuous choice case. We first fit the empirical policy function of investment using a neural network to improve the flexibility of functional forms. Using estimated policy functions and state transition parameters, we forward-simulate equilibrium paths of the dynamic investment game and approximate the expected value functions for states of interest. The states include visited states on firms' equilibrium paths and deviated paths with one-step difference from their choice of action in data. With approximated value function gradients, we convert firms' optimality conditions in each dimension of the multi-product portfolio investment into a joint likelihood function and recover cost parameters using maximum-likelihood estimation (MLE).

Our estimates imply that middle-income households view the purchase and rental of lower-priced homes as close substitutes. With ownership prices bid up and rental supply expanded by institutional landlords, a larger share of these households rents. Cost estimates reveal substantial economies of scope and density, driving landlords' spatial clustering in expansion. Our estimates also indicate a low supply elasticity of homes for purchase, inducing landlords to spread their investment across periods and locations to mitigate the upward pressure on acquisition costs.

Counterfactual analysis reveals mixed welfare effects of institutional landlords' expansion. In primary markets, renter shares increase by 1.58%. Over the years, the welfare gain is \$50.17 per renter year, with 84.04% benefiting from the expansion of rental supply and 15.96% losing due to diminished access to their preferred affordable ownership options. Remaining buyers incur a net loss of \$31.35 per buyer year from inflated ownership prices. Economies of scope and density achieved by institutional landlords' expansion reduce maintenance costs by 60.03%. We conclude that endogenous cost efficiencies play a central role in driving housing supply reallocation, a mechanism amplified when investors are forward-looking.

Related Literature. This paper is the first to build and estimate a dynamic equilibrium model to analyze the expansion and welfare impacts of institutional landlords in the single family home market. Their rapid growth has attracted increasing attention from policymakers, prompting investigations into potential impacts on housing affordability and market functioning. Reduced-form studies have documented causal effects of the presence of institutional landlords on housing market outcomes (Garriga et al., 2020; Gurun et al., 2022) and neighborhood gentrification (Austin, 2022), leveraging local exposure to landlord merger events as exogenous treatment. There is a growing strand of papers using structural methods to study the equilibrium effects of institutional landlords, emphasizing different channels of their impact. Barbieri and Dobbel (2025) study the potential market power of institutional landlords in pricing, as a static equilibrium outcome conditional on (i) exogenous housing supply structure and fixed institutional landlords' holdings, and (ii) exogenous total demand allocated to the rental market and the ownership market. They find limited pricing power, implying that short-run market concentration alone may not explain large market changes. Motivated by this insight, we examine investment dynamics as a distinct mechanism, highlighting (i) endogenous evolution of housing supply shaped by institutional landlords' dynamic investment choices, and (ii) flexible demand substitution within and across renting and buying. Existing research on institutional landlords' investment treats costs as an exogenous static variable (Coven, 2025), as a time-series trend declining over time (Gorback et al., 2025), or as a static choice made by a single global investor (Chang, 2024). We instead, explicitly model the formation of landlord cost efficiency as a series of strategic choices made in interactions with market conditions and competition landscapes. Given the inelastic supply of homeownership and other frictions, housing markets evolve gradually with rich intertemporal trade-offs in decision making, which are better captured in a dynamic framework.

More broadly, this paper adds to the literature of industrial organization in housing markets.

Existing literature have brought demand estimation methods to various contexts with housing or neighborhood choices (Bayer et al., 2007, 2016; Calder-Wang, 2021; Almagro et al., 2024; Calder-Wang and Kim, 2024; Cook et al., 2025), with most applications focusing on either the rental or the home purchase market. This paper proposes an integrated market including both rental segment and ownership segment, modeled using nested logit, providing a stylized yet effective way to capture substitution across tenure types, which is relevant to welfare implications when households re-optimize their tenure choices[2]. In addition, this paper contributes to a growing literature on endogenous housing supply structure. Examples include Diamond et al. (2019) on rental supply responses upon expansion of rent control in San Francisco; Farronato and Fradkin (2022) and Calder-Wang (2021) on the rise of short-term rental supply when the Airbnb platform arrives. This paper investigates the long-term housing stock conversion from the owner-occupied segment to the rental segment through firms' dynamic investment. The framework can be generalized to study a broader range of real estate investment problems.

Our findings highlight the role of dynamically-formed economies of scope and density in driving institutional landlords' expansion in the single-family home market. Existing literature have documented the presence and evolution of economies of scale, scope, and density in retail chains (Jia, 2008; Holmes, 2011; Ellickson et al., 2013), newspaper circulation (Fan, 2013), transportation networks (Chen, 2024), and online platforms' distribution networks (Houde et al., 2023). We extend the literature to housing markets featuring inelastic supply of homes for purchase in each period. Given this, we provide an analysis on the optimal timing of cost efficiency formation, which is less studied in previous work. In contexts with local resource constraints, fast densification of network is penalized with rising costs in investment, which is more prominent when multiple firms compete for the constrained resources to densify their networks in the same location. To mitigate congestion costs, optimal expansion strategies tend to spread smaller-scale investments over multiple periods and spatially differentiate their investments from competitors.

This paper is the first to allow both endogenous costs and benefits of dynamic investment to be determined through a market. Endogenous investment costs are relevant in industries with scarce inputs. For instance, Hsiao (2025) assumes rising marginal costs of plantation development to reflect congestion in factor markets. In the buy-to-rent context, we explicitly model the property acquisition cost through housing market equilibrium. This framework allows congestion to be determined flexibly by supply and demand elasticities, capturing richer incentives in investment strategies when investors compete for scarce resources.

Methodologically, this paper builds on the literature on dynamic estimation (Hotz et al., 1994; Bajari et al., 2007; Pakes et al., 2007; Ackerberg et al., 2007). Following Bajari et al. (2007) (henceforth BBL), a rich body of empirical literature has explored moment inequalities to estimate

[2] Examples include Han et al. (2022) on property transaction tax's impacts on housing tenure choices, and Greenwald and Guren (2025) on quantifying the level of housing market segmentation by tenure.

games with dynamic agents and discrete choices (Ryan, 2012; Collard-Wexler, 2013; Fowlie et al., 2016; Caoui et al., 2022). Less has been studied for continuous choices in dynamic games, with the exception of Barwick et al. (2025), which analyzes industrial policies' implications on shipbuilding investment. This paper contributes the first application to continuous investment problems in spatial competition, where heterogeneous firms optimize by adjusting the densities of their networks over a finite grid of discrete locations. Computational tractability has been a main obstacle for estimating continuous choice equilibrium models. [3] In this paper, we ease the burden by interpreting firms' interior choice of investment in each product type as an interior optimal solution, which yields necessary conditions for optimality that we leverage to estimate dynamic parameters[4]. This method can be generalized to a broader set of problems studying continuous-choice network competition between firms operating in a spatial context. Furthermore, following Sweeting (2013) on radio stations and Bodéré (2023) on pre-schools, we micro-found payoff flows in dynamic problems with static market equilibrium, featuring rich heterogeneity in demand and flexibility in supply specification. We contribute a fully endogenous payoff flow example with both investment costs and per period returns determined by the static equilibrium.

2 Background and Data

2.1 The Rise of Institutional Landlords in Single-family Home Markets

Institutional participation in the single-family housing market grew sharply in the aftermath of the 2008–2009 financial crisis, when foreclosure waves created large inventories of real-estate-owned (REO) properties available for bulk purchase. The phenomenon was most evident in the Sun Belt metropolitan areas, where the pre-crisis housing bubble had been more pronounced and the correction correspondingly more severe. The opportunity of acquiring discounted properties at scale attracted the earliest wave of institutional investment, as these investors held a relative advantage in access to capital and financing. Later on, as the regional economy gradually recovered, inland Sun Belt markets—including Atlanta, Dallas, and Charlotte—experienced strong job growth that attracted middle-income, working-age households and young families. This migration increased demand for affordable housing and contributed to the stabilization of local housing markets. Given the trends, many institutional investors transitioned from short-term asset purchases to developing long-term single-family rental portfolios, consolidating their holdings into large-scale landlord entities. After ten-year sustained acquisitions, institutional owners held roughly 450,000 rental homes nationwide by 2022, which represent a modest share of the total single-family housing stock but a high prevalence in selected Sun Belt metropolitan areas.

[3] Recent advances in methods include Gowrisankaran and Schmidt-Dengler (2024), providing computable methods for a capacity game with many ordered choices and dynamic oligopolies.

[4] See discussions of using first-order conditions to estimate dynamic models in Berry and Compiani (2022)

We make two clarifications about the scope of this paper. First, this paper focuses on the long-term expansion of institutional landlords. Questions on the initial rise of these landlords are beyond the scope of this paper, see Mills et al. (2019) and Hanson (2022) for more discussions. Second, to the best of our knowledge, there is no official criterion that defines an institutional landlord. For clarity, in this paper we define institutional landlords in Atlanta as large corporate owners managing rental portfolios of over 1,000 single-family homes in the area by 2022, along with previously active large corporate landlords that were subsequently acquired or merged into these entities. Figure 1 summarizes the evolution of portfolio sizes for the institutional landlords studied in this paper.

2.2 Institutional landlords' Rental Business Model

Institutional landlords acquire, renovate, and lease single-family homes. When acquiring properties, they typically pay the lump sum ownership costs with cash, instead of using mortgage financing, which allows transactions to close quickly. Since 2014, institutional landlords have shifted from acquiring foreclosure sale homes to buying homes from the retail markets, where most home sellers are owner-occupiers, followed by local homebuilders and small corporate owners. Many institutional landlords work with local real estate agents and brokerage networks to search for suitable homes listed for sale. By 2022, purchases from the ongoing market have accounted for more than 90% of their rental stock.

Post acquisition, institutional landlords undertake a period of renovation to convert homes in varying conditions into rental properties ready for leasing. Renovation involves interior and exterior repairs and replacements, painting, landscaping, and compliance with local building and rental codes. Eligible rental homes are then offered to tenants through leasing platforms, tagged as standardized branded rental products. Despite differences in operational procedures across firms, institutional landlords exhibit broadly similar patterns of property management. Most employ centralized administrative systems, such as digitized lease processing, automated rent collection, and property condition monitoring, and implement standardized leasing and maintenance protocols. These practices enable firms to manage geographically dispersed portfolios of single-family homes efficiently and to deliver consistent service quality at scale.

The rapid growth of large institutional landlords in the U.S. single-family housing market has generated significant policy interest, from federal agencies to local jurisdictions. For instance, a 2024 Government Accountability Office report reviews the expansion of institutional ownership in the single-family rental sector and discusses its potential effects on home prices and rents, though it finds the evidence on home-ownership opportunities and tenant welfare inconclusive due to data limits (U.S. Government Accountability Office, 2024). Despite this heightened attention, few national-level policies currently aim either to restrain or to encourage institutional participation in the

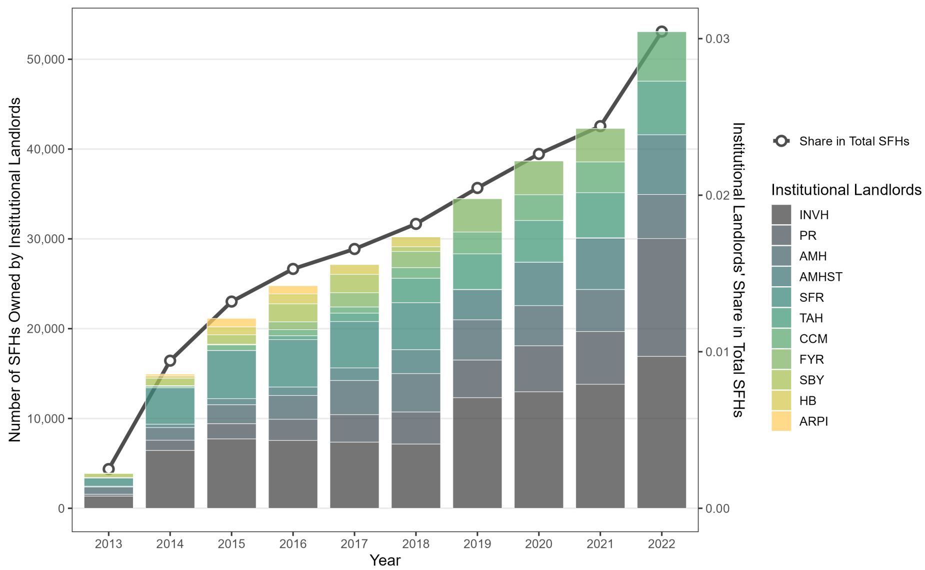


Figure 1: Evolution of Institutional Landlords' Single-family Home Stock
Atlanta MSA 2013-2022

Notes: Figure shows the evolution of single-family home stock owned by institutional landlords in the Atlanta metropolitan area from 2013-2022. Colors indicate landlord identities. The gray curve presents the trend of institutional landlords' share in total single-family home stock. Data source: CoreLogic deeds and manually collected institutional ownership data (procedure described in 2.3.1).

single-family rental market.

2.3 Data Sources

2.3.1 Property Ownership Panel

Our primary data is a comprehensive panel of property ownership history for the universe of single-family homes in Atlanta metropolitan area from 2011-2022. We construct the panel by linking two data sources, CoreLogic property tax data and property deeds, at the property level using unique identifiers. For each property, annual tax data informs the property type, land use code, property characteristics, year of built, property street address, property tax payment, assessed value, and tax payer's mailing address. For each transaction of property ownership, we observe the sale amount, sale date, multi-property sale indicator, and public information on sellers and buyers. Importantly, we observe corporate sellers' and buyers' names and leverage them to track institutional landlords' participation in ownership transactions.

By merging property transaction record with tax history, we partition a property's history into periods owned by different owners. For each period, we classify each property's ownership status into three types: $\{OO, SL, IL\}$, short for owner-occupied, small landlord, and institutional landlord, using the following criteria: [5] [6]

In a given tax year, a property is identified as a rental property, if

1. Mailing address of the tax payer differs from the property address, AND
2. Mailing address is not a mortgage lender's address

For a rental property, we further identify its institutional ownership using buyer's information from its most recent transaction. Institutional investors use subsidiaries to buy properties, making it challenging to identify the ultimate ownership of these properties. To address the issue, we assemble public information on corporate property buyers and sellers from multiple data sources, including institutional investors' historical SEC filings, Georgia Corporations Division Business Search, and OpenCorporates.[7] On top of these, a rental property's ownership can change post mergers between two institutional landlords.[8] To capture the changes, we refine the ownership panel construction using data from the SDC Platinum Mergers & Acquisitions Database.

We include newly constructed properties in the panel data one year before its first-time sale to the market. We label its initial ownership status as NEW, before it is sold to a buyer in one of the three types $\{OO, SL, IL\}$.

2.3.2 Rental Listings and Prices

We obtain rental listing prices from the Altos Multiple Listing Service (MLS) data, which represents a sampling from the universe of rentals at a given period. Overall, the Altos data covers approximately 25% of all single-family homes for rental in the Atlanta metropolitan area[9]. We process the rental prices to two levels. For stylized facts generation, we use the property-level rental prices associated with property characteristics[10]. For demand estimation, we use the median of rental prices for all units listed in MLS for a given type to represent the type level rental price. For home

[5] If a property's indicated status changes under the same owner, we adopt the most frequent tenure-owner status to represent the property's overall status during the consecutive years within the same ownership period. Common reasons for the change include new homeowners continuing to use their previous residence's address for tax mailing purposes for the first several years after move-in, until they eventually update it to their current residence.

[6] Under this criteria, properties under flipping status are labeled as either owner-occupied or for-rental, based on whether the flippers use the property's address for mailing address. We believe the noise introduced by this specification is not going to change the conclusion of this paper for the following reasons: (1) properties under flipping each year account for a relatively small fraction (less than 4%) of Atlanta's SFH stock; (2) the distribution of flipping activities is not significantly different in single-family houses for-rental versus for owner-occupied.

[7] We provide a summary of subsidiaries in Table E.1.

[8] During the period of study from 2011-2022, we document 5 primary M&As between institutional landlords. American Residential Properties → American Homes 4 Rent (2015), Starwood Waypoint Homes → Invitation Homes (2017), Silver Bay Realty → Tricon American Homes (2017), HavenBrook partners → Front Yard Residential (2018), and Front Yard Residential → Progress Residential (2020).

[9] There are two main reasons for the missing rental price data. First, properties with renewed leases remain in the rental market but are not relisted on the MLS until the current contract expires. Second, many rental units are leased through non-MLS channels, a practice especially common among small local landlords.

[10] If a property is listed for multiple times within a year, we adopt the last observation of its price from the last listing record in a year to represent its price of the year.

types with rental prices missing in some years, we fill with interpolated prices using observed prices from adjacent years.

2.3.3 Demographics

We use the American Community Survey (ACS) Public Use Micro Sample to obtain demographics along with housing choice characteristics for households in the housing population. We define housing population as a subset of local residents who have no homeownership in the area at the beginning of a given year.[11] These households constitute the aggregate housing demand for the period of interest. To capture yearly compositional changes in the housing population, we use ACS 1-year estimates. [12] Demographic variables of interest include household income, age, education, number of children, race and ethnicity. Housing choice characteristics include a single-family home indicator, number of bedrooms, housing tenure statuses, and monthly housing costs.

2.3.4 Summary Statistics

Table 1 presents descriptive statistics on the single-family home stock and ownership structure across 20 counties in the Atlanta metropolitan area in 2022. Overall, the majority (79.92%) of single-family homes are under owner-occupancy, followed by small landlords' holdings (16.25%). Institutional landlords' holdings account for a small fraction (3.24%) of the single-family housing stock, with their presence varying greatly across different counties. Five county markets (Paulding, Henry, Douglas, Newton, and Fulton South) have more than 5% of SFH stock under institutional ownership. Around 90% of institutional landlords' holdings are located in half of the twenty counties, led by Gwinnett (18.2%), DeKalb (12.2%), Cobb (11.5%), Henry (10.1%), Paulding (7.74%), Clayton (7.18%), Fulton South (6.16%), Douglas (5.79%), Cherokee (4.36%), Newton (3.90%), and Atlanta City (2.19%). These counties are primarily inner-ring suburbs in the Atlanta metropolitan area. Table 2 provides summary statistics on demographics and survey-reported housing costs for housing population across markets. We observe rich compositional heterogeneity in housing population across markets. Housing costs vary by tenure types: overall the market-mean housing costs as an owner is higher than the costs as a renter, and renting a single-family home in general is more costly than renting other housing types.

[11] We rely on two ACS survey questions to identify a household's initial homeownership status: (i) within one year migration and (ii) homeownership. A household is in previous year's housing population if moving into the current house within one year, or, currently renting the house, or both.

[12] ACS 1-year estimates provide annual updates on a subset of Public Use Micro Areas (PUMAs) with populations of 65,000 or more. All PUMAs in Atlanta MSA are included in the ACS 1-year estimates panel.

Table 1: Summary of Single-family Home (SFH) Stock, Atlanta MSA 2022

Counties	SFH Units (Total)	SFH Types (Physical)	Owner-occupied Shares (%)	Small Landlord Shares (%)	Institutional Landlord Shares (%)	New Construction Shares (%)
Barrow	29,513	17	81.32	14.83	2.19	1.66
Bartow	35,343	25	75.20	22.34	1.85	0.61
Carroll	38,409	21	76.23	21.40	1.32	1.05
Cherokee	84,871	45	81.24	15.59	2.72	0.44
Clayton	82,087	29	72.07	23.08	4.64	0.22
Cobb	207,857	113	86.06	10.81	2.94	0.19
Coweta	51,243	25	82.53	14.77	1.57	1.14
DeKalb	204,634	93	78.22	18.27	3.17	0.34
Douglas	46,666	21	76.28	16.64	6.57	0.51
Fayette	40,543	13	87.27	11.00	0.85	0.89
Forsyth	86,232	24	84.32	13.36	1.02	1.30
Fulton (North)	87,738	57	77.62	21.71	0.33	0.34
Fulton (South)	61,755	25	71.10	22.72	5.29	0.89
Gwinnett	243,592	132	81.16	14.26	3.95	0.63
Henry	79,287	37	80.09	11.71	6.74	1.46
Newton	38,636	13	75.83	18.45	5.35	0.37
Paulding	60,029	20	78.49	14.27	6.83	0.41
Rockdale	29,805	17	77.56	18.37	3.68	0.39
Walton	34,227	16	79.36	18.23	1.34	1.07
Atlanta City	94,521	67	79.85	18.66	1.23	0.26
Total	1,636,988	767	79.92	16.25	3.24	0.59

Notes: The table summarizes the composition of single-family home stock for 20 counties in the Atlanta metropolitan area. Remaining counties in the metropolitan area are excluded from analysis for data quality issues or lack of institutional landlords presence by 2022. We report statistics for Fulton County in three parts: Fulton (North), Fulton (South), and Atlanta City. The division is commonly used in local municipal planning documents and MLS area references.

Table 2: Summary of Housing Population Demographics and Housing Costs across Markets, Atlanta MSA 2022

Statistics	Min	Median	Max
Housing Population Demographics			
Mean of Household Income ($)	62,151	78,961	122,578
Mean of Household Head Age	41.3	44.3	49.6
Share: Bachelor's Degree or Higher	0.194	0.361	0.713
Mean of Children per Household	0.312	0.914	1.21
Share: White, Non-Hispanic	0.049	0.333	0.671
Share: Black/African American	0.079	0.409	0.804
Share: White, Hispanic	0.036	0.105	0.248
Share: Asian	0.000	0.018	0.207
Housing Costs			
Mean of Owner Cost ($/month)	1,279	1,766	2,849
Mean of Rent (SFH, $/month)	911	1,293	2,068
Mean of Rent (non SFH, $/month)	737	1,274	1,709

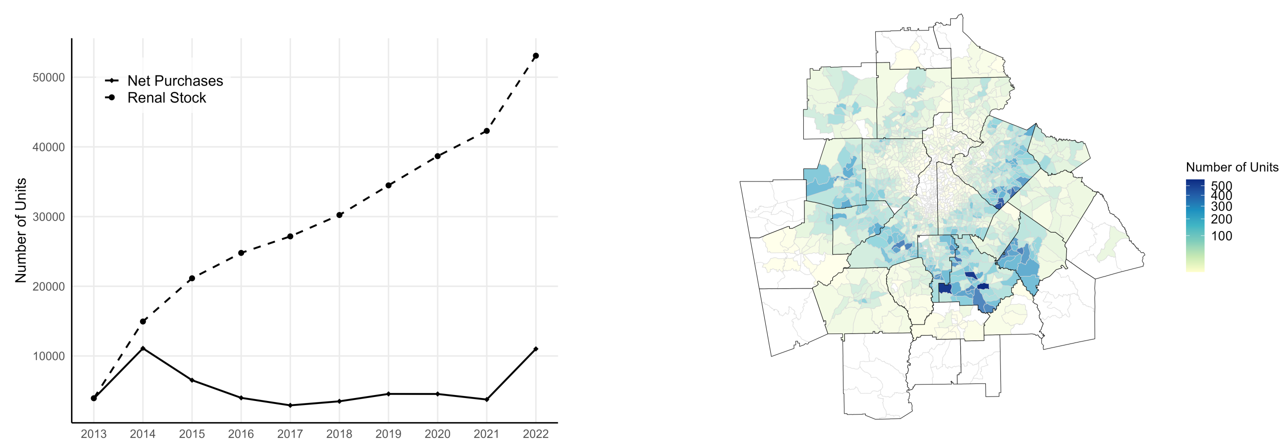
Notes: The table summarizes demographics and housing costs across 20 markets for housing population only. Summary statistics are reported to reveal cross-market variation. See Table E.2 for a comprehensive summary for each market. Data source: American Community Survey Public Use Microdata Sample (PUMS).

3 Stylized Facts

This section presents stylized facts on institutional landlords' expansion that motivate our modeling choices.

Fact 1: Institutional landlords have grown rapidly, converting homes for purchase into rentals throughout the Atlanta metro area. Figure 2(a) show that institutional landlords grow their rental stock from around 4,000 to 53,000 from 2013-2022, through sustained conversion of homes for purchase into rentals. They participate in 3-11% of year-round home purchases with notable fluctuations across years. By 2022, they account for 15% of the total rental supply in the Atlanta primary single-family home market. Figure 2(b) presents the geographical distribution of institutional rentals by 2022. 512 (or 41.4%) census tracts in Atlanta MSA have more than 50 rental homes owned by institutional landlords. This motivates our modeling choice of a dynamic process in which institutional landlords keeps adjusting the size and composition of their portfolios, through repeated interactions with both ownership and rental segments in the local housing market.

Figure 2: Institutional Landlords' Purchases and Rental Portfolio Growth, Atlanta MSA 2013-2022



(a) Number of Units in Purchases (Solid) and in Rental Stock (Dashed)

(b) Institutional Landlords' Rentals across Census Tracts, 2022

Notes: Panel (a) shows the yearly net purchase of home units by institutional landlords (solid), and the resulting updates on institutional landlords' rental stock (dashed). Panel (b) shows institutional landlords' rental stock distribution across counties (bold boundaries) in Atlanta MSA in 2022. Colors represent the number of units in institutional landlords' holdings at census tract level (light boundaries).

Fact 2: Institutional landlords spatially cluster their investments and differentiate from competitors in target location choices. Looking into the geographical distribution of institutional landlords' rental portfolios, we document a common tendency among landlords to spatially cluster their investment. Table 3 reveals portfolio densification from 2013-2022. A rental home's local density equals 25 if its landlord operates 25 properties within 1 mile from the home of interest. Under this specification, by 2022, 65.8% of institutional landlords' rentals are managed in property networks with greater than 25 local density, marking a drastic increase from 2.7% in 2013.

Table 3: Share of Institutional Landlord Rentals by Local Density Ranges (%), Atlanta MSA

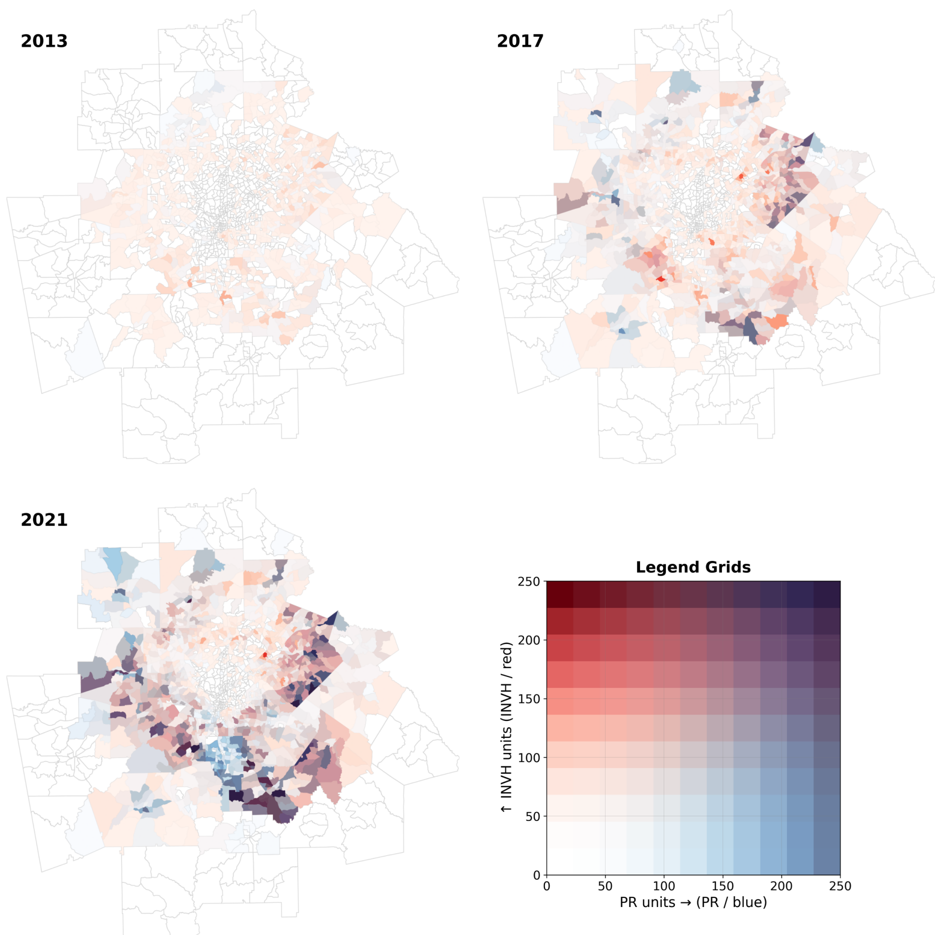
Local Density	[1,25)	[25, 50)	[50, 100)	[100,150)	[150, 200)	200+
2013	97.32	2.68	0.00	0.00	0.00	0.00
2014	70.62	21.81	7.13	0.44	0.00	0.00
2015	65.37	22.90	10.50	1.06	0.17	0.00
2016	64.50	22.76	11.00	1.56	0.18	0.00
2017	63.23	23.38	11.26	1.96	0.16	0.00
2018	50.48	24.09	18.43	4.53	1.84	0.63
2019	48.38	24.28	19.22	4.91	2.40	0.80
2020	45.20	25.09	20.37	5.89	2.19	1.25
2021	39.88	25.69	22.31	7.14	3.54	1.45
2022	34.25	24.16	24.33	9.21	4.59	3.47

Notes: We measure the local density for a home in a landlord's network using the number of total homes managed by the same landlord within 1 mile distance from the home of interest. We then categorize rental homes by how dense their local network is and display the share of each density range and its evolution across years.

Furthermore, institutional landlords spatially differentiate from one another in their strategies of establishing network density. Figure 3 snapshots the geographic expansion of the two largest institutional landlords—Invitation Homes (red) and Progress Residential (blue)—every four years since 2013. The maps show steady expansion and densification by both firms. the two firms' networks exhibit partial overlaps with substantial extent of spatial differentiation. Invitation Homes began earlier with a larger initial stock. Progress Residential entered later and expanded into locations that were less invested by Invitation Homes. By 2021, both firms had expanded across multiple county markets, exhibiting distinct geographic strongholds: Invitation Homes established denser networks in the northeastern and southeastern parts of the metro areas, whereas Progress Residential established denser clusters in the southern and northwestern parts of the metro areas. This pattern suggests firms' incentives to reduce direct competition in home acquisitions and to avoid direct rivalry with their competitors.

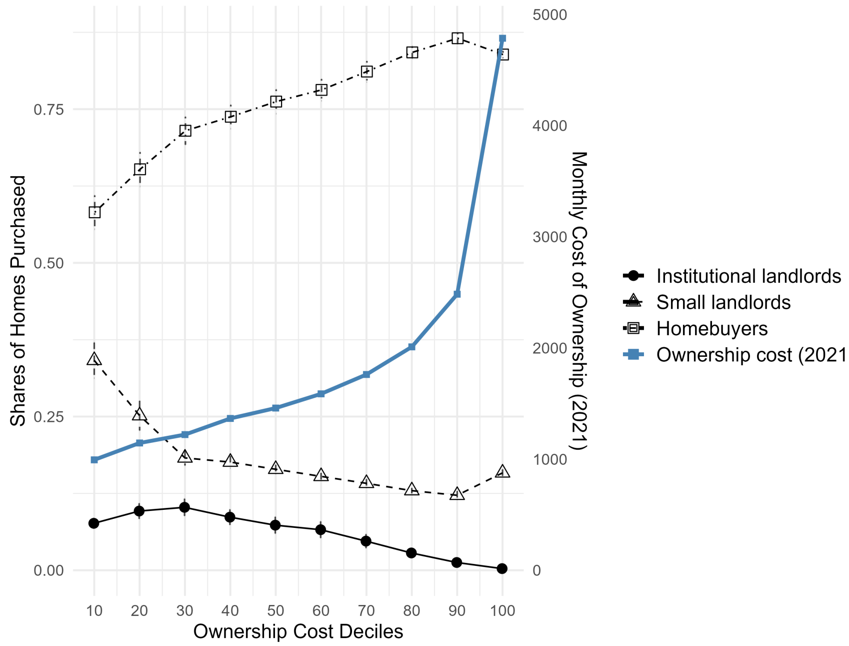
Fact 3. Institutional landlord rentals are primarily converted from homes in lower price ranges. Beyond spatial strategies, institutional landlords further concentrate their investment in lower-priced homes. Figure 4 shows the prevalence of three different types of buyers in home ownership transactions across homes' ownership cost deciles. Institutional landlords' acquisitions are concentrated in the lower-cost segments, with their presence peaking around the 20th–30th deciles and declining sharply thereafter. This pattern indicates several demand-driven incentives in landlords' investment strategies. Institutional landlords enter more in the segment of affordable

Figure 3: Expansion Maps of Invitation Homes (Red) and Progress Residential (Blue)
Atlanta MSA 2013, 2017, and 2021



Notes: We snapshot the spatial expansion of the two largest institutional landlords in Atlanta metropolitan area, Invitation Homes (Red) and Progress Residential (Blue) in 2013, 2017, and 2021. Color gradients (from light to dark) represent the total number of units owned by the two firms at census tract level. Color temperature indicates the relative dominance in stock between two firms: warmer (red) tones indicate areas dominated by Invitation Homes, while cooler (blue) tones indicate areas dominated by Progress Residential.

Figure 4: Buyer Type Prevalence across Home Price Deciles, Atlanta MSA 2013-2021



Notes: This figure shows the prevalence of buyer types across price segments in homeownership transactions. Transactions are grouped by sale price deciles within each year's market. For each decile, we report the share of homes purchased by individual homebuyers (squares), small landlords (triangles), and institutional landlords (solid points). The blue curve plots the median monthly ownership cost for each price decile using 2021 data. Data source: CoreLogic deeds.

houses, competing primarily with budget-constrained individual buyers, who tend to be more price-sensitive than households choosing among high-end housing options. Meanwhile, when converting into rentals, rental options of affordable houses can be more attractive to the group of budget-constrained households, compared to rentals offered to the higher-end of the market, where rentals are less of a substitute for purchase among wealthier households.

Fact 4: Institutional landlords' expansion is correlated with price, quantity, and participant composition changes in both the home ownership segment and the rental segment. We examine the correlational effects of institutional landlords' expansion on various housing market outcomes. Table 4 summarizes the regression results controlling for bedroom type-tract fixed effects and year fixed effects. In homeownership transactions, institutional landlords' presence is correlated with higher prices: a 100% increase of institutional buyers' share in a specific home type is associated with 30.4% increase in its sale price. Also, their purchases are correlated to larger transaction volumes (supply of homeownership): one more unit purchased by institutional landlords is associated with an additional 0.744 homes transacted on the market. Furthermore, the presence of institutional landlords correlates with compositional changes among non-institutional buyers. In home types more heavily targeted by institutional buyers, the decline in individual homebuyers exceeds that of small landlord buyers. This pattern suggests heterogeneous price elasticities in ownership demand between the two groups. Also, it motivates the modeling choice of allowing substitution across renting and buying. If households consider substituting across tenure types, the expansion of rental supply by institutional landlords will further strengthen their incentives to shift away from buying, consistent with the empirical evidence.

In rental markets, one more unit bought by institutional landlords is correlated to 0.663 more units in total rental supply, regardless of landlord types. A 100% increase of institutional share in buyers is associated with 27.8 percentage point increase in institutional landlords' share in rental supply. The correlational effects on rental prices are smaller in scale. A 100% increase of institutional share in buyers of a specific home type is correlated to 3.23% decrease in its rental prices, if operated by small landlords. Given the same physical home type, institutional rentals on average are 3.95% higher in rental prices than its counterpart supplied by small landlords, indicating differences in rental service qualities. Suggested by this, in demand specification we model institutional landlords' rentals as differentiated products from their counterparts supplied by small landlords.

Table 4: Summary of regressions on housing market outcomes

	Ownership Transactions			Rental Market		
Outcome Variables	log(price)	transaction volume	homebuyer share in non-IL buyers	log(rent)	rental supply	Δ IL share in rental supply
Share bought by IL	0.304***		−0.0364*	−0.0323**		0.278***
	(0.0228)		(0.0158)	(0.0114)		(0.0070)
Num. bought by IL		0.744***			0.663***	
		(0.0496)			(0.0240)	
Indicator: IL products				0.0395***		
				(0.0017)		
Bedroom × Tract FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Adj. R^2	0.626	0.823	0.358	0.699	0.344	0.478
Num. obs.	1,122,581	71,608	71,468	501,376	70,903	70,903
Level of obs.	unit	type	type	unit	type	type

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. The table reports OLS estimates of the effects of institutional landlords' investment on housing market outcomes. Regressions in Columns (1) and (4) are conducted at the home unit level. Regressions in Columns (2), (3), (5),and (6) are conducted at the home type level. All regression models include bedroom-tract fixed effects and year fixed effects.

4 Structural Model

We develop an industry model depicting the evolution of a single-family home market. Compared to previous housing market models, our framework differs in two ways. First, we explicitly model the evolution of housing ownership structure using a dynamic game, in which institutional landlords make investment decisions to adjust their rental portfolios.[13] Second, in each period's static housing market equilibrium, we integrate the ownership and rental segments on both the demand and supply sides. On the demand side, we allow for substitution within and across tenure types. On the supply side, rental supply is updated through transactions in the ownership segment. Together, these elements yield a tractable and comprehensive framework for analyzing the long-run effects of landlord investment on the local housing market.

4.1 Static Demand and Supply of Single-Family Homes

Market, product, and characteristics. We define the housing population in market mt as the mass of households entering or living in county m with no home ownership at the beginning of year t[14]. Products in the market are housing options h. Each inside option h aggregates single-family home units sharing physical characteristics, ownership types, and landlord types. We assume housing products are differentiated up to the home type level. Observable characteristics include: number of bedrooms, neighborhood walkable indicator, access to good schools, and PUMA location indicator. Ownership type distinguishes buying from renting. Landlord type is either small landlord or institutional landlord[15]. The specification results in 792 single-family home types and 2,117 inside housing option types in Atlanta 2022. Outside option $h = 0$ is defined as non-single family housing options in the county.

Preferences. (Heterogeneous Coefficient Nested Logit model) Households make a discrete choice of housing across options from three nests (g): homes for rent, homes for purchase, and outside options. Household i's utility from housing type h in market mt is given by:

$$u_{ihmt} = \alpha_{d(i)} p_{hmt} + X_{hmt}\beta_{d(i)} + \xi_{hmt} + \varsigma_{igmt} + (1-\sigma)\epsilon_{ihmt} \tag{1}$$

where p_{hmt} denotes the monthly cost of housing option h. For homes for-sale, p_{hmt} includes mort-

[13] In the empirical dynamic games literature, the closest to this modeling approach are Sweeting (2013) in his study of radio stations and Bodéré (2023) in his study of preschools. Our framework differs in (i) allowing the supply structure of differentiated housing options to be shaped by firms' continuous choice of investment, instead of firms' discrete choices of formats (radio station) or quality (preschool); (ii) modeling multi-product firm strategies in the context with spatial differentiation.

[14] We treat different counties in Atlanta as separate housing markets for two reasons. First, Georgia counties are geographically large, each encompassing a rich set of housing options. Second, Atlanta is recognized as a polycentric metropolitan area (Goulbourne and Schuetz (2021)). With multiple employment subcenters spread across the suburbs, local commuting patterns rarely converge exclusively on the Atlanta City and housing search happens more within the county of work or nearby.

[15] We assume homogeneous landlord services among rental products provided by all institutional landlords

gage interest, property insurance, and property tax payment conditional on home's transaction price[16]. For homes for-rental, p_{hmt} is the monthly rental payment measured using the median of rental listing prices. ξ_{hmt} denotes home type-level unobservable qualities. Finally, the household-home type level shock is composed of group-level common shock ς_{igmt} and idiosyncratic shock ϵ_{ihmt} following type I extreme value distribution. We assume common nesting parameter across nests, $\sigma_g = \sigma, \forall g$, where $\sigma \in [0, 1)$. Households of different demographics $d(i)$ vary in coefficients for monthly costs and a subset of housing option characteristics - number of bedrooms, indicator for home ownership, and indicator for single-family homes. Specification is given by

$$\alpha_d = \alpha_0 + Z_d \pi^{\alpha} \tag{2}$$

$$\beta_d = \beta_0 + Z_d \pi^{\beta} \tag{3}$$

where demographics Z_d include household income, race and ethnicity, age, education, and number of children. We denote the mean utility of housing type h among households in demographic group d as $\delta_{h,d} = \alpha_d p_h + X_h \beta_d + \xi_h$.

Given supply in each housing type S_h, household i's probability of choosing type h is,

$$s_{h,d(i)} = \frac{S_h \exp\left(\frac{\delta_{h,d(i)}}{1-\sigma}\right)}{D^{\sigma}_{g,d(i)} \left[\sum_g D^{(1-\sigma)}_{g,d(i)}\right]} \tag{4}$$

$$\text{where} \quad D_{g,d(i)} = \sum_{h' \in g} S_{h'} \exp\left(\frac{\delta_{h',d(i)}}{1-\sigma}\right) \tag{5}$$

We denote the distribution of demographics in the housing population as P_D and the size of housing population as M. The demand for type h aggregated from household choices is given by

$$D^{hhd}_h = M \cdot \int s_{h,d}(z)\, dP_D(z) \tag{6}$$

Static supply. We model the supply of home ownership S^O and small landlord rentals S^{R-sl} as part of the static housing market equilibrium, conditional on the dynamic choices of investment by institutional landlords.

Supply of home ownership is composed of new constructions and units for-sale from the existing housing stock. We assume an exogenous flow of new constructions, S^{O-new}_{hmt}. For supply from incumbent home owners, we model them as aggregations of individual potential seller's probability of selling given market conditions in mt and allow flexible patterns across incumbent owner occupiers

[16] Appendix B.2 presents more details in ownership cost construction.

and incumbent small landlords. The aggregated supply functions are

$$S_{hmt}^{O-oo} = g^{(1)}(p_{hmt}^{O}, \nu_{hmt}^{oo}; \theta^{s}) \cdot Q_{hmt}^{oo} \tag{7}$$

$$S_{hmt}^{O-sl} = g^{(2)}(p_{hmt}^{O}, p_{hmt}^{R-sl}, \nu_{hmt}^{sl}; \theta^{s}) \cdot Q_{hmt}^{sl} \tag{8}$$

In Equation 7, we allow incumbent owner occupiers' selling probabilities to respond to home prices. This incorporates a home owner's incentive of capitalizing the property and relocate when the property value increases. In Equation 8, we allow incumbent small landlords' selling probabilities to be jointly determined by $(p_{hmt}^{O}, p_{hmt}^{R-sl})$. This is micro-founded by an incumbent small landlord's optimal stopping problem where p_{hmt}^{O} and p_{mt}^{R-sl} enter the exit value and continuation value respectively.

Similarly, we model the demand for home ownership from potential small landlord entrants as an aggregation of entry probabilities. Potential entrants are assumed to be tied to a given home type h, choosing between entering as a landlord or staying out. We assume the choice probabilities to be jointly determined by $(p_{hmt}^{O}, p_{hmt}^{R-sl})$. The aggregated demand is

$$D_{hmt}^{O-sl} = g^{(3)}(p_{hmt}^{O}, p_{hmt}^{R-sl}, \nu_{hmt}^{sl}; \theta^{s}) \cdot S_{hmt}^{O} \tag{9}$$

Net purchases by small landlords in year t update the stock of small landlord rentals in year $t+1$,

$$Q_{hmt+1}^{R-sl} = Q_{hmt}^{sl} - S_{hmt}^{O-sl} + D_{hmt}^{O-sl} \tag{10}$$

where Q_{hmt}^{sl} represents the number of homes owned by small landlords when year t begins. In the rental sector, we assume zero vacancy rates for landlords of all types. Hence, $Q_{hmt+1}^{R-sl} = S_{hmt+1}^{R-sl}$.

Static market clearing. Conditional on institutional landlords' investment a_{hmt} and the resulting updated institutional landlord rentals, S_{hmt+1}^{R-il}, the static housing market equilibrium in mt is solved by a set of prices $\mathbf{P}_{mt} = \{(p_{hmt}^{O}, p_{hmt+1}^{R-sl}, p_{hmt+1}^{R-il})\}_{h \in \mathcal{H}}$ that clears demand and supply for each home type h across all ownership and landlord types.

$$S_{hmt}^{O-new} + S_{hmt}^{O-oo}(\mathbf{P}) + S_{hmt}^{O-sl}(\mathbf{P}) = D_{hmt}^{O,hhd}(\mathbf{P}) + D_{hmt}^{O-sl}(\mathbf{P}) + a_{hmt} \tag{11}$$

$$S_{hmt+1}^{R-sl}(\mathbf{P}) = D_{hmt+1}^{R-sl,hhd}(\mathbf{P}) \tag{12}$$

$$S_{hmt+1}^{R-il} = D_{hmt+1}^{R-il,hhd}(\mathbf{P}) \tag{13}$$

4.2 Institutional Landlords' Problem

On top of the static housing market described in Section 4.1, local housing stock evolves in its size and ownership structure, shaped by (i) new construction flows, (ii) ownership transactions between incumbent homeowners and incoming households and small landlords, and (iii) institutional landlords' investment over time. In this section, we present a dynamic equilibrium model of landlord investment, in which landlords are dynamic investors, adjusting their rental portfolios by choosing the number and types of homes to buy to maximize the value of their from the portfolio.

State space, actions, and timing. Landlords are indexed by j. We denote $(\mathcal{M}_{mt}, \xi_{mt})$ as the set of observed and unobserved market-level state variables common to all landlords. $\mathcal{M}_{mt}$ includes the size and demographic composition of the housing population, $(M, P_D)_{mt}$, the size and ownership structure of non-institutional housing stock $Q^{\Lambda}_{mt} = \{Q^{\lambda}_{hmt}\}_{h\in\mathcal{H},\lambda\in\{oo,sl,new\}}$, size of non-single family home stock Q_{0mt}, property-management wage w_{mt+1}, mortgage rates and property tax rates $(r^{\text{mtg}}_t, r^{\text{tax}}_{mt})$, and observable characteristics of a time-invariant grid of homes, $\{X_h\}_{h\in\mathcal{H}}$. ξ_{mt} represent the unobservable demand shocks $\{(\xi^{O}_{hmt}, \xi^{R-sl}_{hmt+1}, \xi^{R-il}_{hmt+1})\}_{h\in\mathcal{H}}$.

Apart from common states, landlord j faces landlord-specific state variables $(Q_{jmt}, Q_{-jmt}, \nu_{jmt})$. Q_{jmt} is an $H \times 1$ vector summarizing landlord j's holdings of units in each home type $h \in \mathcal{H}$. Q_{-jmt} is a matrix recording the holdings of each competitor landlord $-j$ in each home type h. In each period, landlord j faces private action-specific shocks in investment cost, $\nu_{jmt}(a)$, capturing unobserved private costs associated with j's investment process.

In year t, given existing stock Q_{jmt} and other state variables,landlord j chooses the number of homes to purchase or sell in each type h, denoted by $a_{jmt} = \{a_{jhmt}\}_{h\in\mathcal{H}}$. We model a_{jhmt} as a continuous choice variable taking values from $\left[-Q_{jhmt}, Q^{\text{total}}_{hmt} - Q_{jhmt}\right]$, where $Q^{\text{total}}_{hmt} = \sum_{\lambda\in\{oo,sl,new\}} Q^{\lambda}_{hmt} + \sum_j Q_{jhmt}$ represents the total housing stock in type h.[17]

We assume state realizations and actions follow the timing below:

1. Year t starts. Market-level states $(\mathcal{M}_{mt}, \xi_{mt})$ are realized. Landlord j begins with existing stock $\{Q_{jhmt}\}_{h\in\mathcal{H}}$ and observe all competitor landlords' stocks $\{Q_{-jhmt}\}_{h\in\mathcal{H}}$.

2. Private investment cost shocks are revealed to landlord j, $\nu_{jmt}(a)$. Landlord j chooses the number of units to purchase or sell across home types, $a_{jmt} = \{a_{jhmt}\}_{h\in\mathcal{H}}$, updating its rental stock to $Q_{jhmt+1} = Q_{jhmt+1} + a_{jhmt}, h \in \mathcal{H}$.

3. Housing market in t opens with landlord j's choice included in the aggregate demand for ownership a_{mt}, which updates the supply of institutional landlord rentals S^{R-il}_{mt} together with other landlords' choices. Ownership and rental options are transacted at market-clearing prices $\mathbf{P}_{mt} = \{(p^{O}_{hmt}, p^{R-sl}_{hmt+1}, p^{R-il}_{hmt+1})\}_{h\in\mathcal{H}}$. Flow payoff for landlord j in year t Φ_{jmt} is realized. Non-institutional housing stock ownership structure evolves to

$$Q^{\lambda}_{hmt+1} = Q^{\lambda}_{hmt} - S^{O,\lambda}_{hmt} + D^{O,\lambda}_{hmt}, \quad \lambda \in \{oo, sl\}$$

[17] Table E.5 summarizes the frequency of a_{jhmt} values in sample. a_{jhmt} ranges from below -5 to above 25 across firms, types and market-years. Given the wide dispersion in observed values, we treat the integer choices as continuous, which captures the main patterns while keeping the model tractable.

4. Year t ends. Market-level exogenous state variables evolve to the next period following exogenous transition processes.

Flow Payoffs. In year t, landlord j faces investment costs composed of lump-sum payment for homes purchased in t and action-specific cost shocks,

$$c^I_{jmt}\left(a_{jmt}, \nu_{jmt}\left(a_{jmt}\right)\right) = \sum_h a_{hjmt} p^O_{hmt} + \nu_{jmt}\left(a_{jmt}\right) \tag{14}$$

where we make two assumptions on $\nu_{jmt}(a_{jmt})$ to facilitate estimation.

Assumption 1: $\nu_{jmt}\left(a_{jmt}\right) = \sum_h \nu_{jmt}(a_{hjmt})$

Assumption 2: $\nu_{jmt}(a_{hjmt}) = a_{hjmt}\ p^O_{hm0}\ \nu_{jhmt},\ \nu_{jhmt} \sim^{\text{iid}} N(0, \sigma^\nu)$

Assumption 1 implies that action-specific cost shocks from the portfolio are additively separable across home types in the portfolio, with each term depending exclusively on within-type h's investment level. Assumption 2 further implies that type-level investment shocks aggregate unit-level shocks, each proportional to the property's value in period 0. Intuitively we assume that property of higher values exhibits larger absolute volatility in its realized prices[18].

By choosing investment a_{jmt}, landlord j adjusts its rental portfolio to Q_{jmt+1} and receives rental profits from year $t+1$. We make a further assumption on landlord j's supply of rental:

Assumption 3: $S^{R-il}_{jmt+1} = Q_{jmt+1}$

Assumption 3 implies a zero vacancy rate in landlord j's rental stock: conditional on investment, landlord j are rental price takers, supplying every unit of its holdings to the rental market. Under Assumption 3, the model rules out the exercise of market power through pricing — that is, landlords are not allowed to withhold homes from the rental market to raise rents and increase profits.[19] Landlord j's rental profit is given by

$$\pi_{jmt+1} = \sum_{h \in \mathcal{H}} \left(p^{R-il}_{hmt+1} - \text{avc}_{jhmt+1}\right) Q_{jhmt+1} \tag{15}$$

where avc_{jhmt} is the average variable cost for j to manage a rental unit of type h in market $mt+1$. To capture potential economies of scope and density in the provision of rental services, we model cost in two parts: the baseline cost and cost multipliers shifted by portfolio scope and density. We measure portfolio scope using the total number of homes operated by landlord j in county m[20].

[18] A standard assumption in asset pricing literature, see Black and Scholes (1973)

[19] According to public information disclosed by representative institutional landlords, their rental portfolios exhibit small vacancy rates. Quarterly reports from Invitation Homes and American Homes 4 Rent show that the unit-level occupancy rates range from 95-98% with seasonal fluctuations, exceeding the Georgia state average. This suggests a non-central role of mark-up to vacancy tradeoff in institutional landlords' strategies. By making assumption 3, we block the channel of pricing from all subsequent welfare calculations. Barbieri and Dobbel (2025) study the margin of market power in pricing by institutional landlords and conclude limited presence of market power in this context.

[20] In Atlanta Metropolitan Areas, most administrative processes relevant to rental portfolio management - such as property taxation, eviction filings, code enforcement, and deed recording - are organized at the county level. We

For each rental home h in the portfolio, we measure the local density using the total number of homes operated by landlord j in the same geographical subdivision (PUMA) as that of home h, $\mathcal{H}_{\text{puma}(h)} = \{h' \in \mathcal{H} : \text{puma}(h') = \text{puma}(h)\}$. To summarize, the average cost function is given by

$$\text{avc}_{jhmt+1} = \left(\gamma_0 + \gamma_1 w_{mt+1} + \gamma_2 p^{O,\text{lump sum}}_{hmt}\right) \cdot \left[(\frac{\tilde{Q}^{\text{total}}_{jmt+1}}{100})^{\gamma_3} + \gamma_4 \left(\frac{\tilde{Q}^{\text{local}}_{hjmt+1}}{100}\right)^{\gamma_5} \right] \tag{16}$$

where

$$\tilde{Q}^{\text{total}}_{jmt+1} = \sum_{h' \in \mathcal{H}} Q_{jh'mt+1} \tag{17}$$

$$\tilde{Q}^{\text{local}}_{hjmt+1} = \sum_{h' \in \mathcal{H}_{\text{puma}(h)}} Q_{jh'mt+1} \tag{18}$$

where w_{mt+1} is the median wage of employees in the real estate leasing industry in county market $mt+1$. $p^{O,\text{lump sum}}_{hmt}$ is the lump sum home ownership price for type h in mt. The baseline cost is modeled to capture labor inputs in the provision of rental services and the part of maintenance costs proportional to property's market value, including tax and insurance payments. Furthermore, the specification in Equation 16 assumes a constant rate of cost reduction across homes with different baseline costs, conditional on fixed portfolio scope and density.

To wrap up, landlord j's payoff flow from year t is the sum of investment costs in t and discounted rental profits from $t+1$.[21]

$$\begin{aligned}
&\Phi_{jhmt}\left(a_{jhmt}, a_{-jhmt}, Q_{jhmt}, Q_{-jhmt}, \nu_{jhmt}, \mathcal{M}_{mt}, \xi_{mt}\right) = \\
&-\textstyle\sum_h p^O_h\left(a_{jhmt}, a_{-jhmt}, Q_{jhmt}, Q_{-jhmt}, \mathcal{M}_{mt}, \xi_{mt}\right) a_{jhmt} + p^O_{hm0}\nu_{jhmt}\, a_{jhmt} && \text{(investment cost)} \\
&+12\beta \textstyle\sum_h \Big(p^{R-il}_h\left(a_{jhmt}, a_{-jhmt}, Q_{jhmt}, Q_{-jhmt}, \mathcal{M}_{mt}, \xi_{mt}\right) && \text{(rental revenue)} \\
&\qquad - avc_j(a_{jhmt}, a_{-jhmt}, Q_{jhmt}, Q_{-jhmt}, \mathcal{M}_{mt}, \xi_{mt})\Big)\left(Q_{jhmt} + a_{jhmt}\right) && \text{(maintenance cost)}
\end{aligned}$$

State transitions. We denote the full set of landlord j's state variables as (s, ν) where s are the public state variables perceived by j and ν is j's private action-specific shocks. The transition process $f\left(s_{jmt+1}, \nu_{jmt+1} \mid s_{jmt}, \nu_{jmt}, a_{jmt}, \sigma_{-j}\right)$ is given by:

therefore use counties as the boundaries for landlord scope measurement. More regulatory details are available in the O.C.G.A. § 44-2-1 (2024) and Georgia Landlord–Tenant Handbook, Georgia Department of Community Affairs.

[21] Note that landlord j's rental revenue in $t+1$ is determined with certainty conditional on landlord j's investment choice in t, competitor landlords' choices in t, and housing market equilibrium solved in t. By including wage w_{t+1} in market-level state $\mathcal{M}_t$, landlord j's rental profits from $t+1$ is a function of a_{jt}, a_{-jt} and state variables in t only.

$$f\left(s_{jmt+1}, \nu_{jmt+1} \mid \cdot\right) = f\left(s_{jmt+1} \mid \cdot\right) f\left(\nu_{jmt+1}\right) \qquad \text{(i.i.d. } \nu \text{ shocks)} \tag{19}$$

The transition of s_{jmt} is composed of multiple parts. The housing stock ownership structure transits following

$$\begin{aligned} f\left(Q_{jmt+1}, Q_{-jm,t+1}, Q^{\Lambda}_{mt} \mid \cdot\right) &= f\left(Q_{jmt+1} \mid a_{jmt}, Q_{jmt}\right) f\left(Q_{-jmt+1} \mid \cdot\right) f\left(Q^{\Lambda}_{mt} \mid \cdot\right), \text{where} \\ f\left(Q_{jmt+1} \mid a_{jmt}, Q_{jmt}\right) &= \mathbf{1}\left\{Q_{jmt+1} = Q_{jmt} + a_{jmt})\right\} \end{aligned} \tag{20}$$

landlord j's stock is updated deterministically conditional on the investment choice. (Q_{-j}, Q^{sl}, Q^{oo}) evolves following competitor's policy functions and the resulting equilibrium ownership transactions. We assume that landlord j expects the current corporate ownership of institutional landlords to persist and treat future merger events as unexpected exogenous shocks.[22] For new constructions, Q^{new}, we model the flow and its evolution as exogenous time series parameterized with θ^{trans}. Among the environment variables, all evolves exogenously following processes parameterized with θ^{trans} except the housing population variables $(M, P_D)_{mt}$, depicting the size and demographic distribution of the housing population in mt. Housing population is jointly determined by the exogenous flow of net in-migration M^0_{mt+1} and the endogenous flow of housing population retention from previous periods, with the latter shifted by the size and composition of renters solved in period t's equilibrium.

$$M_{mt+1} = \eta \sum_{h} \left(D^{R-sl,hhd}_{hmt+1} + D^{R-il,hhd}_{hmt+1}\right) + M^0_{mt+1} \tag{21}$$

where η is the (broad) retention rate of renters, defined as the probability for a renter household to join next year's housing demand in the same county[23].

Optimality conditions. With revealed action-specific private shocks ν_j, landlord j's optimal investment vector solves:

$$\max_{a_j} \ \mathbb{E}_{\nu_{-j}}\left[\Phi_j\left(a_j, \sigma_{-j}\left(s_{-j}, \nu_{-j}\right), s_j, \nu_j\right) + \beta \mathbb{E}\left[V^{\sigma}_j\left(s'_j\right) \mid a_j, \sigma_{-j}\left(s_{-j}, \nu_{-j}\right), s_j, \nu_j\right]\right] \tag{22}$$

where $a_j = (a_{1j}, a_{2j}, \ldots, a_{Hj})$. Under strategy profile σ, we denote the ex-post value function as $V^{\sigma}(s, \nu)$ and ex-ante value function as $V^{\sigma}(s)$. In Equation 22, the outer expectation is taken over private shocks to competitors $-j$. The inner expectation is taken over shocks in state transitions

[22] See similar assumptions in Sweeting (2013).

[23] In estimation, we estimate the empirical transition process of $(M, P_D)_{mt+1}$ as as whole, which is part of the equilibrium with presence and expansion of institutional landlords and changes little when landlord j makes marginal deviation in investment choices. In counterfactual study, we first calibrate the exogenous flows of $(M, P_D)_{mt+1}$ with parameter η, then construct counterfactual series of $(M, P_D)_{mt+1}$ for equilibrium banning institutional landlords from expansion.

to s'. The interior solution of a_{hj} satisfies

$$0 = -p^O_{h0}\,\nu_{hj} + \mathbb{E}_{\nu_{-j}}\left[-p^O_h + \beta(p^R_h - \text{avc}_{jh}) - \mathbf{a}_j^\top \underbrace{\nabla_{a_{hj}}\mathbf{p}^O}_{\substack{\text{inflated cost}\\ \text{of investment}}} + \beta(\mathbf{Q}_j + \mathbf{a}_j)^\top \Big(\underbrace{\nabla_{a_{hj}}\mathbf{p}^R}_{\substack{\text{rent decrease}\\ \text{and spillovers}}} - \underbrace{\nabla_{a_{hj}}\mathbf{avc}_j}_{\substack{\text{cost benefits}\\ \text{and spillovers}}} \Big) + \beta\frac{\partial EV^\sigma_j(s')}{\partial a_{hj}}\right] \tag{23}$$

Equality holds for all optimal choices of a_{hj} ranging between $-Q_{hj} < a_{hj} < Q^{\text{total}}_h - Q_{jh}$: landlord is not selling all its holdings in type h, and is not buying all units in the existing stock of type h.
Equilibrium concept. A Markov-Perfect Equilibrium of this model is,

1. a matrix of prices $\mathbf{P}_{mt} = \{(p^O_{hmt}, p^{R-sl}_{hmt+1}, p^{R-il}_{hmt+1})\}_{h\in\mathcal{H}}$
2. a matrix of housing stock by ownership $Q^\Lambda = \{Q^\lambda_h\}_{h\in\mathcal{H},\lambda\in\{oo,sl,new\}}$ and institutional landlords' holdings, $\{Q_{hjmt}\}_{h\in\mathcal{H},j\in\mathcal{J}}$
3. a policy function σ_j for each institutional landlord j in investment

such that,

1. given prices $\mathbf{P}_{mt}$ and housing supply $\left(S^O, S^{R-sl}, S^{R-il}\right)_{hmt}$, households make their optimal housing choices, forming aggregated demand $\left(D^{O,hhd}, D^{R-sl,hhd}, D^{R-il,hhd}\right)$.
2. given competitors' strategies σ_{-j} and realized states, each institutional landlord j optimally invest following policy function σ_j to maximize their value functions, forming aggregated demand D^{O-il} and updating rental supply to S^{R-il},
3. given prices $\mathbf{P}_{mt}$ small landlords decide optimally on entry/exit, aggregating to ownership demand D^{O-sl}, ownership supply S^{O-sl} and rental supply S^{R-sl}. Incumbent home owners decide optimally on selling/keeping their houses, aggregating to ownership supply S^{O-oo}.
4. prices $\mathbf{P}_{mt}$ clear the market:

$$S^{O-new}_{hmt} + S^{O-oo}_{hmt}(\mathbf{P}) + S^{O-sl}_{hmt}(\mathbf{P}) = D^{O,hhd}_{hmt}(\mathbf{P}) + D^{O-sl}_{hmt}(\mathbf{P}) + D^{O-il}_{hmt}$$

$$S^{R-sl}_{hmt+1}(\mathbf{P}) = D^{R-sl,hhd}_{hmt+1}(\mathbf{P})$$

$$S^{R-il}_{hmt+1} = D^{R-il,hhd}_{hmt+1}(\mathbf{P})$$

5 Estimation

We conduct estimation of the structural model in two general steps. First, we use market-level data with micro moments from all county-year's ownership and rental segments to estimate demand parameters in the heterogeneous coefficient nested logit model (Berry, 1994; Berry et al., 1995; Nevo, 2000, 2001; Petrin, 2002; Grigolon and Verboven, 2014; Conlon and Gortmaker, 2025). Second, based on demand estimates, static supply estimates, and transition process estimates, we adapt the two-step framework to the continuous choice context and obtain MLE estimator for cost parameters (Hotz et al., 1994; Bajari et al., 2007; Pakes et al., 2007; Ackerberg et al., 2007).

5.1 Estimating Housing Demand Parameters

Identification. There exist three sources of endogeneity in the housing demand system. First, endogenous prices $\mathbf{P}_{mt}$, rooted from their correlation to unobserved quality ξ_{mt}. In sorting equilibrium, holding all else fixed, market-clearing prices tend to be lower for housing products with unobservably lower qualities. Second, endogenous supply of housing in both ownership segment S^{O-oo}, S^{O-sl} and rental segment S^{R-sl}, S^{R-il}. For supply determined by local small landlords and incumbent owner-occupiers, their probabilities of supply are functions of endogenous prices. For supply determined by institutional landlords, the unobserved qualities ξ_{mt} are part of their state variables, shifting their investment choices and in turn, their rental supply. Third, the endogenous within-nest shares of housing types $s_{h|g}$. Within the same nest and all else fixed, housing types with higher unobserved qualities will have higher within-nest shares.

To address the price endogeneity, we use an identification strategy that leverages the cross-market variation in supply structure across housing types, following Berry et al. (1995) and Bayer et al. (2007). The relevance condition holds, because holding all else fixed, a house will have a higher price in the sorting equilibrium if the supply of its close substitutes is more scarce. Given endogenous supply in our context, we further refine the argument by replacing real supply terms with fitted values of supply, predicted by exogenous variables only. To conclude, the conditions used to identify linear demand parameters are:

$$\forall h: \quad g_h(\tilde{\mathbf{P}}, X^{\text{exog}}, \tilde{S}, \xi = 0, P_D; \theta^D) = s_h \tag{24}$$

$$\mathbb{E}\Big[\xi \tilde{\mathbf{P}}\Big] = 0 \tag{25}$$

$$\mathbb{E}[\xi X^{\text{exog}}] = 0 \tag{26}$$

where g_h is the expectation of households' aggregated share of choosing type h under candidate demand parameter θ^D, s_h is the observed share of type h aggregated from households' choices in data. Equation 24 specifies a model-generated instrument $\tilde{\mathbf{P}}$ that solves the real-world market shares with two key differences: $\xi = 0$ and exogenous fitted value of supply, $\tilde{S}$. By construction, $\tilde{\mathbf{P}}$ satisfies the exclusion restriction and is a valid instrument for price.

To identify the nesting parameter, we use home type-level housing stock as an exogenous instrument to shift within-nest shares. Identification leverages the cross-market variation attributed to new constructions and changes in outside options. We denote house type h as $(\overline{h}, k(h))$, where $\overline{h}$ represents the physical type h belongs to, and $k(h) \in \{O, R-sl, R-il\}$ represents the owner group. First, $\hat{Q}^{IV}_{hmt}$ is given by $\hat{Q}^{IV}_{hmt} = Q^{total}_{\overline{h}mt} \cdot \gamma^{k(h)}_{m}$, where $\gamma^{k(h)}_{m}$ is the mean rate of supply by owner group $k(h)$ in county m over all types and periods.

$$\hat{s}^{IV}_{h|g,mt} = \frac{\hat{Q}^{IV}_{hmt}}{\sum_{h' \in g} \hat{Q}^{IV}_{h'mt}} \tag{27}$$

The moment is given by

$$\mathbb{E}\left[\xi \hat{s}^{IV}_{h|g}\right] = 0 \tag{28}$$

Apart from endogeneity issues, we further recover households' heterogeneity in tastes by demographics using correlation between households' choice characteristics and households' demographics[24].

Implementation. We construct the model-generated instrument for prices $\tilde{\mathbf{P}}_{mt}$ as follows:

1. Prepare a grid of candidate demand parameters, $\tilde{\Theta}$. In market mt, prepare exogenously predicted supply structure $\{\tilde{S}_h\}_{h \in \mathcal{H}}$, housing option characteristics $\{X_h\}_{h \in \mathcal{H}}$, and size and distribution of housing population, (P_D)

2. Set $\xi = 0$. For each $\theta^D \in \tilde{\Theta}$, solve for prices $\tilde{\mathbf{P}}_{mt}(\theta^D)$ such that $g_h(\tilde{\mathbf{P}}_{mt}, X_{mt}, \tilde{S}_{mt}, \xi_{mt} = 0, P_D; \theta^D) = s_{hmt}$ for all $h \in \mathcal{H}$, where s_{hmt} is the observed share of housing type h formed by households choices only in market mt.

We then use the nested fixed point algorithm to search for the GMM estimator of demand parameters, $\theta^D = (\alpha, \beta, \pi^\alpha, \pi^\beta, \sigma)$. The outer loop searches for nonlinear parameters, $(\pi^\alpha, \pi^\beta, \sigma)$. For each guess of nonlinear parameters, we calculate the demographic-specific parts of the utility and invert market shares to recover the mean utility of each housing type. Given mean utility, in the inner loop we obtain linear IV estimates of (α, β) (conditional on the guess of nonlinear parameters). Instruments used include exogenous housing type characteristics, X^{exog} and price instruments, $\{\tilde{\mathbf{P}}_{mt}(\theta^D)\}_{\theta^D \in \tilde{\Theta}}$. We use an initial guess of linear parameters and locate the closest candidate on grid, θ^{grid-D}_0 and the corresponding instrument $\tilde{\mathbf{P}}_{mt}(\theta^{grid-D}_0)$. Using this, we obtain the IV estimates θ^{IV-D}_1 and use it to update the closest candidate on grid, θ^{grid-D}_1, and iterate until the difference between iterations closes to below tolerance criteriaFinally, we calculate the correlation using simulated data, the IV moment for nesting parameter, and the updated GMM objective function value.

Results. We use data from 20 markets in the Atlanta metropolitan area from 2011 to 2021 for demand estimation. Table 5 presents the GMM estimates for (α, β, σ) and Table 6 for (π^α, π^β). Mean

[24] Table E.4 summarizes the correlation between selected demographics and housing characteristics.

utility parameter estimates indicate households' overall preference for larger houses with more bedrooms and neighborhoods with access to more high-quality schools. Households with more children value both aspects more, out of their needs for more space and convenient access to good schooling resources. On average, households prefer less walkable neighborhoods. One explanation is that a large fraction of households in suburban counties owns their cars, therefore the access to amenities such as restaurants and grocery stores is not strictly constrained by neighborhood walkability. Moreover, lower-walkability areas are associated with lower crime rates, fewer disturbances, higher environmental quality, and less compact housing if zoned for lower-density zoning.

Table 5: Parameter Estimates for Single-Family Home Demand

	Estimates	SE
Monthly cost ($1,000)	-11.070	0.371
Three-bedroom	2.150	0.089
Four-bedroom	4.825	0.200
Five and more-bedroom	8.485	0.367
Walkable neighborhood	-0.356	0.060
One high-quality school	1.127	0.060
Two high-quality schools	1.668	0.081
Three high-quality schools	2.272	0.107
Indicator: institutional landlord	1.483	0.056
Indicator: ownership	-8.551	0.158
FEs: geographical division (PUMA)	X	
FEs: county market SFH indicator	X	
σ	0.485	0.650

Notes: This table reports (i) nesting parameter estimate, and (ii) mean utility parameter estimates representing the taste for attributed by the default demographic group (mean log(income), no child, younger than 25 yrs old, no bachelor degree, Race: Others). Figure E.2 provides a map visualization of fixed effects of PUMAs and county-specific single-family homes (over non-single family homes).

Beyond physical attributes, our estimates indicate that households value the quality of services provided by institutional landlords relative to those offered by small local landlords. The positive coefficient has two key implications. First, institutional landlords expand local rental choice sets not only by increasing the number of supply but also by introducing new products served with centralized platforms and professional maintenance networks, thereby generating additional welfare gains. Second, perceived differences in service quality allow institutional landlords to differentiate along the service margin from otherwise similar homes. This further enables them to sustain different market-clearing prices from small landlords. As a result, even in a vacancy-free equilibrium, institutional landlords retain some pricing power through the investment decisions made by a small number of players offering standardized rental products, akin to a Cournot game.

Our estimates reveal rich heterogeneity in households' substitution patterns across buying and

Table 6: Non-linear Parameter Estimates for Single-Family Home Demand

	Monthly cost ($1,000)	Three-bedroom	Four-bedroom	Five-bedroom	Indicator: ownership	Indicator: SFH
log(income)	0.422	0.063	0.143	0.511		-0.454
	(0.281)	(0.082)	(0.161)	(0.737)		(0.495)
Income group: $50k-$100k					0.932	
					(0.432)	
Income group: $100k-$150k					2.014	
					(0.484)	
Income group: $150k-$200k					2.678	
					(0.490)	
Income group: $200k+					3.334	
					(0.629)	
Number of child: 1-2	0.843	0.116	0.158	-0.107	0.996	1.123
	(0.749)	(0.284)	(0.331)	(0.410)	(0.437)	(2.238)
Number of child: > 2	1.198	0.046	0.533	0.519	1.223	1.942
	(1.125)	(0.325)	(0.587)	(0.627)	(0.909)	(2.324)
Age: 25-35	-0.233				-0.029	-0.592
	(1.119)				(1.213)	(1.408)
Age: 35-45	-0.111				-0.252	0.243
	(1.223)				(1.236)	(1.789)
Age: 45-55	-0.013				0.283	0.616
	(1.120)				(1.256)	(2.078)
Age: 55+	-0.221				0.588	0.729
	(1.049)				(1.200)	(1.688)
Bachelor's Degree	1.470				2.520	
	(2.355)				(2.181)	
Race: White, Non Hispanic	1.199				1.512	
	(1.831)				(2.603)	
Race: Black	-2.037				-2.812	
	(6.664)				(7.849)	
Race: White, Hispanic	-0.367				-0.120	
	(4.724)				(6.846)	
Race: Asian	1.040				2.037	
	(1.873)				(2.685)	

Notes: This table reports the parameter estimates for interactions between demographics and households' tastes for a subset of housing attributes.

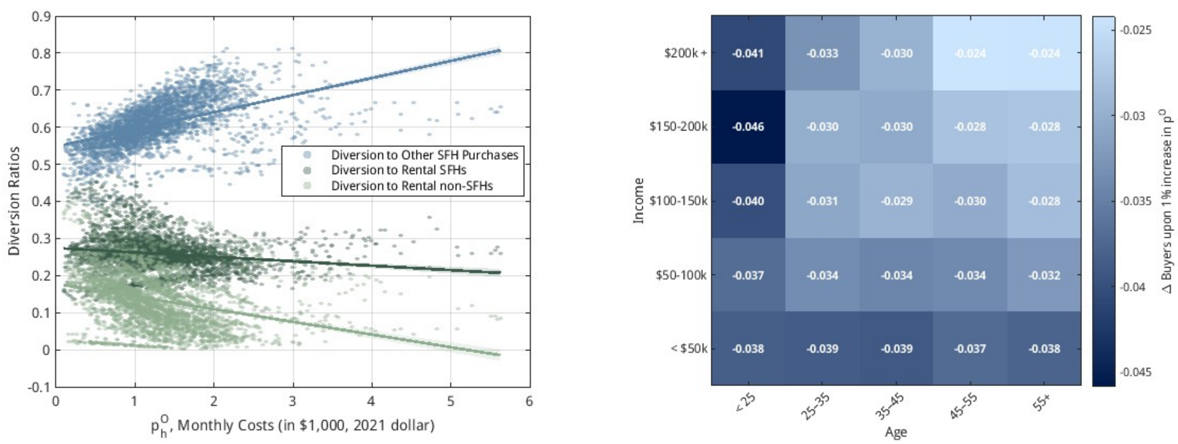
renting. The estimated nesting parameter $\hat{\sigma} = 0.485$ suggests the existence of substitution both within and across buying single-family homes, renting homes, and renting apartments. For the default demographic group, specified as households younger than 25 with mean log annual income and no bachelor's degree or children, buying a home generates net negative utility compared to renting. This reflects the financial burden of a down payment and future mortgage commitments, whish is particularly large for young households with typically low savings. For them, the costs of ownership outweigh the potential benefits, making renting more favorable for affordability and flexibility. In contrast, households with higher income and education, more children, headers aged 45 and above derive higher utility from homeownership. They are less budget constrained and may value more the stability from settling in a location with homeownership. Advantages of homeownership include, hedging against future home price fluctuations, mortgage-related tax advantages, and the accumulation of household wealth from the commitment to long-term saving, which contribute to the net utility gains from homeownership that outweigh the costs.

Table 7: Aggregate Demand Elasticities: Median

	Supply: Real Data		Supply: Adjusted	
	$\%\Delta D^R$	$\%\Delta D^O$	$\%\Delta D^R$	$\%\Delta D^O$
$\%\Delta p^R$	-3.394	2.991	-3.836	2.411
$\%\Delta p^O$	0.622	-3.171	0.881	-2.867

Notes: This table shows the median of demand elasticities (own and cross) from their distributions across markets. The matrix on the left represents results under supply structure fixed at the data level. The matrix on the right represents results under an alternative supply structure, adjusted to facilitate equal total supply in ownership SFH options and rental SFH options. The adjustment is meant to isolate the effects of supply structure and to illustrate preference parameters and their heterogeneity across demographics only. See a full plot of distribution in Figure E.3.

Figure 5: Price Elasticities in Demand: by Ownership Prices and Demographics



(a) Diversion Ratios against Prices

(b) Heterogeneity, Income-Age Bins

Notes: This figure illustrates the demand responses to a 1% increase in ownership options, holding supply fixed. Panel (a) increases ownership prices separately for each home type h and plots the diversion ratios into other ownership options (blue), single-family rentals (dark green), and non-single-family rentals (light green) against the ownership price of type h (monthly cost, in 2021 dollars). Panel (b) increases ownership prices for all home types simultaneously by 1% and shows the corresponding decline in buyers' share, expressed as a fraction of the original buyers' share across income–age groups. Darker bins indicate stronger substitution from buying to renting.

Using demand estimates, we derive own and cross price elasticities of aggregate rental demand and ownership demand for single-family homes. Elasticities vary across markets and form a distribution, attributed to variations in housing population demographics and supply structures in the housing choice set. Table 7 reports the medians. We begin with the calculation using real data supply (see Table 7, Left). Demand for rentals is more price elastic than demand for ownership, primarily driven by demographic differences: buyers are older, higher-income households who are less sensitive to price changes. Cross-price elasticities indicate that the rise in purchase prices generates a smaller percentage increase in rental demand than the opposite way. The pattern is jointly determined by two factors. First, buyers are less price sensitive than renters. Second, shaped by the supply asymmetry, there are more renters than buyers in the sorting equilibrium, limiting the fractional increase in renters when buyers substitute to renting. We isolate the role of demand parameters by redistributing the supply, all patterns hold (see Table 7, Right).

Demand estimation further conveys the demand-side factor that induce institutional landlords to target more at lower-price properties. We define type-level diversion ratios as, upon the increase in home price of type h, the shares of original home buyers substituted away from buying home of type h to buying other homes (blue), renting homes (dark green), and renting apartments (light green). Figure 5 Panel (a) presents home types' diversion ratios against their ownership prices (standardized). When ownership price increases, buyers originally choosing homes from the higher price ranges substitute more to buying other homes, instead of renting. In contrast, more substitution from buying into renting is observed in lower price ranges. When making investment decisions, institutional landlords anticipate a larger fraction of displaced potential home buyers to choose rentals if their investment targets at lower-priced properties, which rationalized the Stylized Fact 3.

5.2 Estimating Other Static Supply and Demand Parameters

We parameterize the static ownership supply functions and small landlords' ownership demand function in Section 4.1 using probit links,

$$S_{hmt}^{O-oo} = \Phi(\log(p_{hmt}^{O,\text{lump sum}}), FE_h, \nu_{hmt}^{O-oo}; \theta_1^S) \cdot Q_{hmt}^{oo} \tag{29}$$

$$S_{hmt}^{O-sl} = \Phi(\log(p_{hmt}^{O,\text{lump sum}}/p_{hmt+1}^{R-sl}), FE_h, \nu_{hmt}^{O-sl,1}; \theta_2^S) \cdot Q_{hmt}^{sl} \tag{30}$$

$$D_{hmt}^{O-sl} = \Phi(\log(p_{hmt}^{O,\text{lump sum}}/p_{hmt+1}^{R-sl}), FE_h, \nu_{hmt}^{O-sl,2}; \theta_3^S) \cdot S_{hmt}^{O} \tag{31}$$

where $\Phi(\cdot)$ is the cumulative distribution function (henceforth cdf) of the standard normal distribution. Parameters of interest are $(\theta_1^S, \theta_2^S, \theta_3^S)$. Prices and rents are endogenous given their correlation to unobservables in the supply system, $\nu^{O-oo}, \nu^{O-sl,1}, \nu^{O-sl,2}$. We leverage instruments that exogenously shift the prices and rents from the demand side, and specifically the variation in demographic distribution in housing population across markets.[25] Table E.3 summarizes the

[25] As defined earlier, housing population refers to the group of households who enter a county's market in a given year with no home ownership. Therefore, their demographic attributes shift prices and rents only from the demand side. For Equation 31, unobservables exist in potential small landlord entrants' demand functions. Demographic instruments are valid too, under the assumption that housing population demographics are exogenous to potential small investors' attributes.

Table 8: Other Static Supply and Demand Parameters

	Coefficients	Estimates	SE
Supply of ownership from OO, S^{O-oo}			
$\log(p^{O,\text{lump sum}}_{hmt})$	θ^S_1	0.125	0.025
FEs: home type		X	
Supply of ownership from SL, S^{O-sl}			
$\log(p^{O,\text{lump sum}}_{hmt}/p^{R-sl}_{hmt+1})$	θ^S_2	0.337	0.057
FEs: home type		X	
Demand of ownership from SL, D^{O-sl}			
$\log(p^{O,\text{lump sum}}_{hmt}/p^{R-sl}_{hmt+1})$	θ^S_3	-2.251	0.156
FEs: home type		X	

Notes: We measure the total ownership price of houses, $p^{O,\text{lump sum}}$ in \$1,000, not including property taxes, mortgage interests, or insurances. We measure the rental prices of homes supplied by small landlords, p^{R-sl} using the monthly rents in \$.

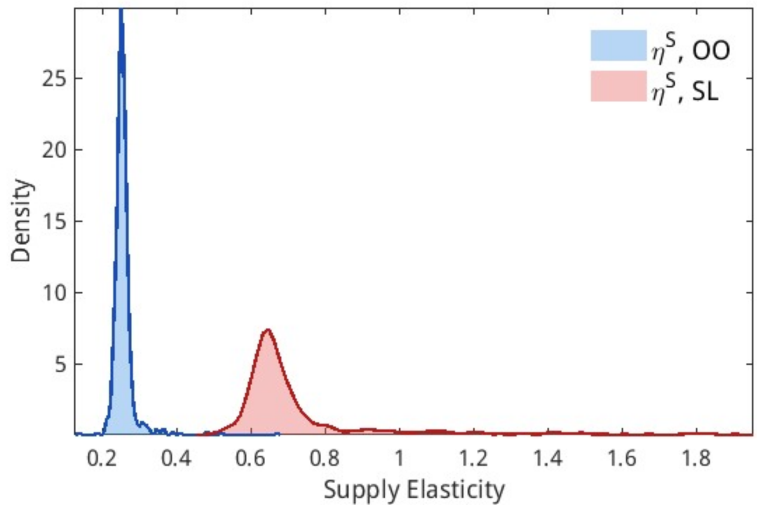
first-stage regression results of these instruments. The F statistic is 58.85 for estimating Equation 29 and is 13.04 for estimating Equation 30 and 31. Table 8 presents the estimates of supply parameters with home type fixed effects controlled. For an incumbent owner occupier, the probability of selling increases by 0.125 given 1% increase in total sale prices. Holding rental prices as fixed, the probability of selling from incumbent small landlords increase by 0.337 given 1% increase in total sale prices. The same price change, to the potential small landlord entrants, will decreases their probability of buying by 2.251. Based on the results, we calculate ownership supply elasticities across home types and plot the distribution in Figure 6. Overall, the ownership supply from existing homes exhibits low elasticity, with notable heterogeneity across sellers. Among incumbent owner-occupiers—the majority of potential sellers—the median supply elasticity is 0.253. Incumbent small landlords display relatively higher elasticity, with a median of 0.659, with greater variance across home types compared to owner-occupier sellers.

5.3 Estimating Institutional Landlord Cost Parameters

We exploit landlords' interior choices of investment a_{hjmt} under varying states to identify the dynamic parameters $\theta^C = (\gamma, \sigma_\nu)$ in their cost functions. Recall Equation 23:

$$0 = -p^O_{h0}\,\nu_{hj} + \mathbb{E}_{\nu_{-j}}\left[-p^O_h + \beta(p^R_h - \text{avc}_{jh}) - \mathbf{a}_j^\top \underbrace{\nabla_{a_{hj}}\mathbf{p}^O}_{\substack{\text{inflated cost}\\ \text{of investment}}} + \beta(\mathbf{Q}_j + \mathbf{a}_j)^\top \Big(\underbrace{\nabla_{a_{hj}}\mathbf{p}^R}_{\substack{\text{rent decrease}\\ \text{and spillovers}}} - \underbrace{\nabla_{a_{hj}}\mathbf{avc}_j}_{\substack{\text{cost benefits}\\ \text{and spillovers}}} \Big) + \beta\frac{\partial EV^\sigma_j(s')}{\partial a_{hj}}\right]$$

Figure 6: Distribution of Ownership Supply Elasticity across Home Types



Notes: The figure shows the distribution of ownership supply elasticities from existing stock of homes, for incumbent owner- occupiers (blue) and small landlords (red) separately. For small landlords, to calculate ownership supply elasticities we hold rental prices as fixed and only make marginal changes to the lump sum ownership prices. Calculation uses estimates in Table 8.

The challenging part in landlord's optimality condition is $\mathbb{E}_{\nu_{-j}}\left[\frac{\partial EV_j^{\sigma}(s')}{\partial a_{hj}}\right]$, which summarizes the expected marginal effect of a_{hj} chosen in one period on the expected continuation value evaluated in the next period. In the multi-agent dynamic game, a full solution of value function is not feasible. Therefore, we follow the BBL two-stage framework to first propose a method of forward-simulation, then apply the method to calculate the $\mathbb{E}_{\nu_{-j}}\left[\frac{\partial EV_j^{\sigma}(s')}{\partial a_{hj}}\right]$ at states of interest. Finally, we assemble the results and develop a maximum likelihood estimator using Equation 23.

First Stage: Neural Network Estimation of Policy Functions. With sufficiently large number of observations, policy functions would be estimated nonparametrically. However, this is not feasible given the dimension and size of the state space with continuous state variables, compared to which the sample size is relatively small. To overcome the challenge, we estimate policy functions using neural network in combination with parametric restrictions to facilitate a balance between flexible functional form and reasonable scale of predictions made at both visited and not-visited states.

The policy function, $\sigma_j(\cdot)$ is a mapping from firm j's state variables to the (dis)investment choice on H differentiated home types. We re-write the choice for each dimension as the product of policy ratio (r^a_{hjmt}) and stock of homes owned by non-institutional landlords. The policy ratio is allowed to be negative.

$$a_{hjmt} = r^a_{hjmt} \cdot (Q^{oo}_{hmt} + Q^{sl}_{hmt} + Q^{new}_{hmt}) \tag{32}$$

Then, we train a neural network model to predict r^a_{hjmt} as a function of a rich set of inputs composed of state variables and functions of state variables. We denote the data generating process of policy ratio as

$$r^a_{hjmt} = g(x_{hjmt}, \nu_{hjmt}), \tag{33}$$

where ν_{hjmt} enters $g(\cdot)$ linearly with $g_\nu < 0$, as guaranteed by landlord j's optimality condition in Equation 23 under Assumptions 1 and 2. We denote the trained neural network model as $\hat{g}^{nnt}(x_{hjmt}; \hat{\theta}^g)$, which predicts the ex-ante expectation of policy ratio that would be chosen by firm j given some realized value of x_{hjmt}, before the realization of cost shocks ν_{hjmt}. To recover the empirical distribution of residual investment driven by the cost cost shocks, we calculate the residuals

$$\hat{\epsilon}^a_{hjmt} = r^a_{hjmt} - \hat{g}^{nnt}(x_{hjmt}; \hat{\theta}^g) \tag{34}$$

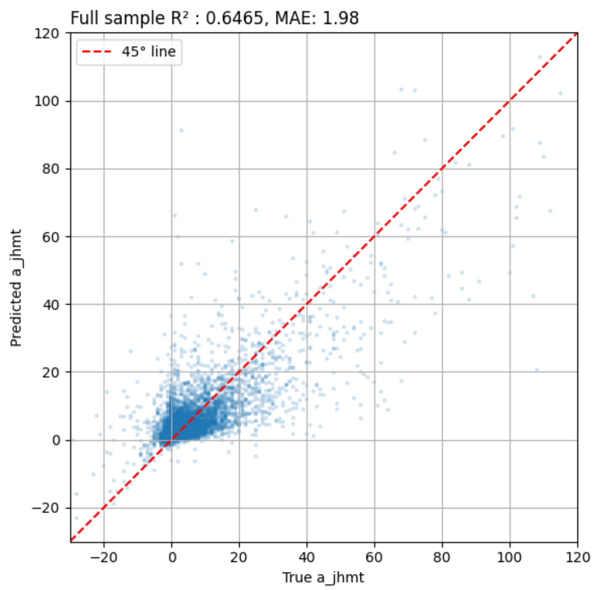
and use the sample variance of $\hat{\epsilon}^a_{hjmt}$ as the sample analog to the variance of the distribution of shock-driven residual investment. The neural network estimates, together with the estimated variance of residuals, will be used in the forward simulation method of approximating value functions to predict firms' investment choices under different realizations of states and shocks. In simulation, investment shocks $\nu_{hjmt} = \nu^*$ and residual investment $\epsilon^a_{hjmt} = \epsilon^*$ are drawn in a joint way, such that

$$F_{\epsilon^a}(\epsilon^*) = 1 - F_\nu(\nu^*) \tag{35}$$

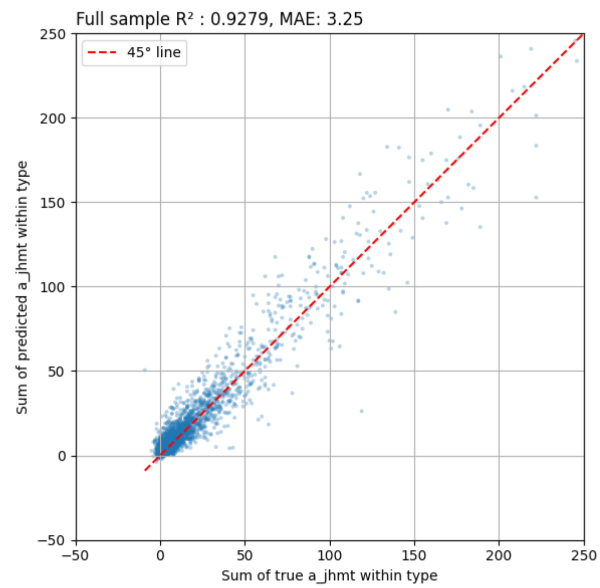
where F_{ϵ^a} is the cdf of residual investment and F_ν is the cdf of investment shock basis.

Figure 7 displays the full sample fit of neural network model with 2 layers of 128/64 units. Panel (a) shows the model fit of firm-home type level investment, comparing $\mathbb{E}_\nu[\hat{\sigma}_{jh}(s_{jmt}, \nu)]$ against $a_{jh} = \sigma_{jh}(s_{jmt}, \nu_{jhmt})$ under some realized value of private shock ν_{jhmt}. Distance from each point to the 45-degree line is the sum of (i) potential model specification error in $\hat{\sigma}_j$ and (ii) private-shock driven residual investment aggregated out when taking expectation. Panel (b) further shows that, when aggregating investment choices over firms in the same market, year, and home type, distances between predicted expectations and real data are notably shortened, with R^2 increases from 0.647 to 0.928. The diminishing distance is mainly driven by part (ii): idiosyncratic firm-type investment shocks aggregate out in sample sums with 5-10 firms, leaving remaining distance primarily attributed to estimation or model specification error in $\hat{\sigma}_j$. Suggested by the good fit in Panel (b), neural network estimation of $\hat{\sigma}_j$ provides reliable first-stage fit of firms' policies.

Second Stage: Forward Simulation and Value Function Approximation. Using estimated policy functions $\hat{\sigma}_j$ and state transition processes $\hat{\theta}^{trans}$, we forward-simulate equilibrium paths starting from a state of interest, which later, will be used to approximate the value function. Given that the dynamic parameters enter flow payoffs linearly, the simulated paths do not depend on the values of these dynamic parameters. Instead, they depend only on estimates from demand, static supply, state transitions, and first-stage fitted policy functions. This substantially reduces the com-



(a) Fit of a_{jhmt}



(b) Fit of $\sum_j a_{jhmt}$

Figure 7: First-stage Fitted Policy Functions $\hat{\sigma_j}$, Neural Network with 2 Layers of 128/64 Units

Notes: We train the neural network model on 80% of the data and leave 20% of the data to test model performance. The neural network model is trained and used to predict investment at firm-home type level, as described in Section 5.3. The figures here show the performance for the full sample. Panel (a) compares a_{jhmt} in data with model-predicted means $\hat{a}_{jhmt}$. Panel (b) compares $\sum_j a_{jhmt}$ with $\sum_j \hat{a}_{jhmt}$, by aggregating investment choices across firms for each home type.

putational burden, allowing second stage estimation to search and evaluate candidate parameters using a fixed set of inputs from forward simulation.

We follow the steps below to approximate $\beta \mathbb{E}_{\nu_{-j}} \left[\frac{\partial EV_j^{\sigma}(s')}{\partial a_{hj}} \right]$.

1. Assume the state of interest is s_{0j} and the optimality condition is derived from the choice of investment by j in type h^*.

2. Starting from $t = 0$, we simulate $N^{\text{sim}} = 500$ paths of length $T^{\text{sim}} = 20$, in which exogenous state variables evolve following transition processes with realized shocks. In $t = 0$, landlord j chooses the investment vector a_{jmt} observed in data. Other landlords $-j$ draw their investment levels following $\hat{\sigma}_{-j}(s_{0,-j})$ and the cdf of realized private shocks on each path. We solve the static housing equilibrium and update the housing ownership structure to next period.

3. For $t = 1, ..., T^{\text{sim}}$, all landlords invest follow $\hat{\sigma}$ and the cdf of the realized private shocks. For each period on the simulation path, we save the equilibrium prices, landlord j's investment choices, private cost shocks, and updated rental stock.

4. Repeat steps 2 and 3 with one change in $t = 0$. In $2'$, landlord j chooses the investment vector with Δa units of deviation from the choice in data in home type h, $a'_{hjmt} = a_{hjmt} + \Delta a$ only

for $h = h^*$. We specify $\Delta a = 1$. Simulate the subsequent equilibrium path given updated choice of investment in h^* by landlord j.

5. Given the two sets of simulation results and candidate parameter θ^C, calculate

$$\beta\overline{V}(s' \mid a_j; \theta^C) = \frac{1}{N^{\text{sim}}} \sum_{i=1}^{N^{\text{sim}}} \sum_{t=1}^{T^{\text{sim}}} \beta^t \Phi_j(a_{jt}, Q_{jt+1}, p_t^O, p_{t+1}^{R-il}, w_{t+1}, \nu_{jt}; \theta^C) + \beta^{T^{\text{sim}}} V^{\text{last}}(Q_{jT+1}, p_T^O, p_{T+1}^{R-il}, w_{T+1}; \theta^C) \tag{36}$$

$$\beta\overline{V}(s' \mid a_j + \Delta a_{h^*}; \theta^C) = \frac{1}{N^{\text{sim}}} \sum_{i=1}^{N^{\text{sim}}} \sum_{t=1}^{T^{\text{sim}}} \beta^t \Phi_j(a'_{jt}, Q'_{jt+1}, p_t^{O,\prime}, p_{t+1}^{R-il,\prime}, w_{t+1}, \nu_{jt}; \theta^C) + \beta^{T^{\text{sim}}} V^{\text{last}}(Q'_{jT+1}, p_T^{O,\prime}, p_{T+1}^{R-il,\prime}, w_{T+1}; \theta^C) \tag{37}$$

where the V^{last} is the continuation value evaluated at T^{sim} as the present discounted value of all future rental profits, assuming no more adjustment to rental stock by any of the institutional landlords starting $T^{\text{sim}} + 1$. We approximate the discounted expectation of value function gradient using:

$$\beta \frac{\partial \overline{V}_j(s'; \theta^C)}{\partial a_{h^*j}} = \frac{\beta\overline{V}(s' \mid a_j + \Delta a_{h^*}; \theta^C) - \beta\overline{V}(s' \mid a_j; \theta^C)}{\Delta a_{h^*}} \tag{38}$$

Second Stage: Optimality Condition and MLE Estimator. For each (s_{jmt}, a_{jhmt}) in data satisfying interior solution condition, $-Q_{jhmt} < a_{jhmt} < Q_{hmt}^{\text{total}} - Q_{jhmt}$, given candidate parameter $\theta^C = (\gamma, \sigma_\nu)$, we can recover the private investment cost shock using sample analog of Equation 23:

$$\hat{\nu}_{hj} = \frac{1}{p_{h0}^O} \left[\frac{1}{N^{\text{sim}}} \sum_{i=1}^{N^{\text{sim}}} \Bigg(-p_{h,i}^O + \beta(p_{h,i}^R - \text{avc}_{jh,i}) - \mathbf{a}_j^\top \nabla_{a_{hj}} \mathbf{p}_i^O + \beta(\mathbf{Q}_j + \mathbf{a}_j)^\top (\nabla_{a_{hj}} \mathbf{p}_i^R - \nabla_{a_{hj}} \mathbf{avc}_{j,i}) \Bigg) \right] + \beta \frac{\partial \overline{V}_j(s')}{\partial a_{hj}} \tag{39}$$

For notation convenience, we denote the recovered $\hat{\nu}_{hj}$ as a function of $Data_{jh}$ and candidate parameters (γ, σ_ν). By Assumption 2, ν_{hj} follows a normal distribution with unknown variance, $N(0, \sigma_\nu^2)$. The negative log-likelihood function is given by

$$\text{NLL}(\gamma, \sigma_\nu) = \frac{N}{2} \log\left(2\pi\sigma_\nu^2\right) + \frac{1}{2\sigma_\nu^2} \sum_{i=1}^{N} \left[\hat{\nu}_{hj}\left(\text{Data}_i; \gamma, \sigma_\nu\right)\right]^2 \tag{40}$$

Results. Table 9 presents results from dynamic parameter estimation. Estimates show that in the baseline cost, labor costs weigh more than the property-value related costs. Estimates quantify the economies of scope and density. $\hat{\gamma}_3 < 0$ and $\hat{\gamma}_4 \cdot \hat{\gamma}_5 < 0$, indicates that average variable costs of maintenance decreases as portfolio size and density grows. Given $\hat{\gamma_3} < 0$ and $\hat{\gamma_5} < 0$, the marginal cost reduction to scope and density are both diminishing. Hence, marginal cost reduction is smaller for firms expanding from a larger and denser site.

Table 9: Dynamic Parameters

	Coefficients	Estimates
Baseline Costs		
Intercept	γ_0	779.414
Wage	γ_1	0.142
Property value (in \$1,000)	γ_2	0.011
Cost Multipliers		
Economies of scope, nonlinear	γ_3	-0.286
Economies of density, linear	γ_4	0.439
Economies of density, nonlinear	γ_5	-0.214
Private Cost Shocks		
Std. Dev.	σ^ν	0.203
Statistics		
Negative Log Likelihood		0.393
Observations		9,929

Notes: Estimation is conducted setting $\beta = 0.92$ and $\alpha^{\text{retention}} = 0.8$. Standard Errors in progress.

6 Assessing Economies of Scope and Density

Using cost function estimates, we recover the firm-property level maintenance costs and their evolution across years. Figure 8 (a) plots the trend of average variable costs, standardized as a fraction of the cost of running one isolated rental unit with no scope or density economies. Along with portfolio expansion, institutional rentals' mean average variable cost decreases from 0.33 to 0.20 with a shrinking standard deviation from 0.11 to 0.05. Figure 8 (c) plots the trend of rental profits per property month. As institutional landlords expand, average rental profits per unit month increase from \$-235.72 to \$300.95 with a shrinking standard deviation from 536.62 to 329.40. In both plots we provide the paths of two firms, Invitation Homes (red dashed) and Amherst (blue dot dashed), to illustrate firm heterogeneity. Given diminishing returns to scope and density indicated by $\hat{\gamma_3}, \hat{\gamma_5} < 0$, marginal cost reduction is smaller for firms expanding from a larger and denser base. Invitation Homes begins with a larger portfolio size and keeps lower-than-industry average costs throughout the years with relatively less reduction in costs. Amherst, in contrast, begin with a smaller portfolio size and high costs, reduces its costs at a relatively fast pace through expansion. Figure 8 (b) supplements an example of a single landlord's evolution in its portfolio size and density.

Color gradients show that average costs decline as portfolio scope and density increase, indicated by $\hat{\gamma_3}, \hat{\gamma_5} < 0$ and $\hat{\gamma_4} > 0$. From year 0 to year 8, we observe overall increases in both portfolio size and density in the majority of locations, resulting in decreases in maintenance costs per unit.

To quantify the margin of cost reduction from portfolio growth, we conduct a counterfactual analysis using landlords' initial portfolio size and densities to calculate the per-unit costs for units in landlords' post-expansion portfolios in Year 8 (2021). We then compare the real costs with the counterfactual costs at the firm-market level. Figure 8 (d) shows that portfolio growth positively contributes to cost reduction. The aggregated cost reduction rate across all firms and primary markets is 60.03%, or $1312.5 per rental unit month in 2021.

7 Welfare Effects of Institutional Landlords' Expansion

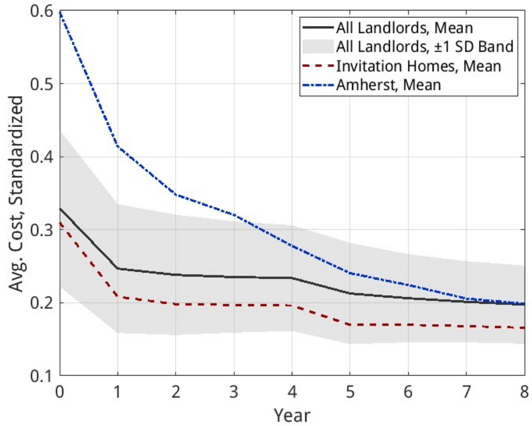
To estimate the effects of institutional landlord's expansion on welfare distribution, we conduct a counterfactual analysis where institutional landlords are prohibited from expansion from 2013 and on. We simulate the housing market equilibrium from 2013 (Year 0) to 2021 (Year 8), excluding institutional landlords from home ownership transactions. We recompute market-clearing prices for ownership options and rental options, quantities transacted, and the equilibrium path of housing ownership structure evolution.

Price Effects. We compare the equilibrium housing prices in each year across paths with and without institutional landlords' expansion. Figure 9 shows the distribution of type-level price differences, for ownership options, small landlord rentals, and institutional landlord rentals. With institutional landlords' expansion, home ownership prices increase to varying extents across a majority of types, as landlords' investment shifts the aggregated demand for ownership outward while aggregated supply elasticity remains at a low level. The scale of price increase in each year is positively correlated to institutional landlords' aggregated number of home acquisitions (see Figure 2 Panel (a)).

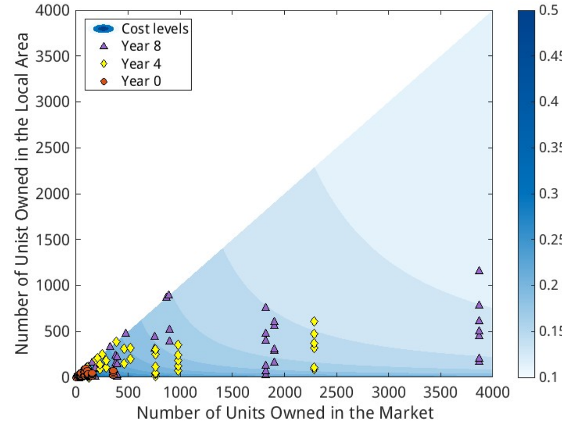
In the rental sector, we find steady yet small-scale[26] decrease in rental prices across years as institutional landlords expand. Institutional landlords' continuing expansion leads to steady growth in the supply of branded rental products, which is both a direct substitute to existing branded rentals and a close substitute to existing small landlords' offerings, differing only in the dimension of landlord service. Therefore, we find downward effects on rents in both sectors. The scale of rent changes is smaller: institutional landlords' expansion induces households to substitute away from buying to renting, given upward pressure on ownership prices. Therefore, rent decrease is constrained by outward-shifting aggregated demand for rentals.

Households Welfare Effects. With nested logit demand specification, household i's compensa-

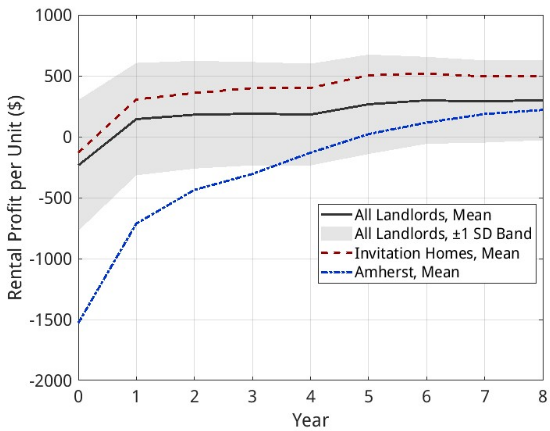
[26]Smaller both in dollar terms and as a fraction of counterfactual prices.



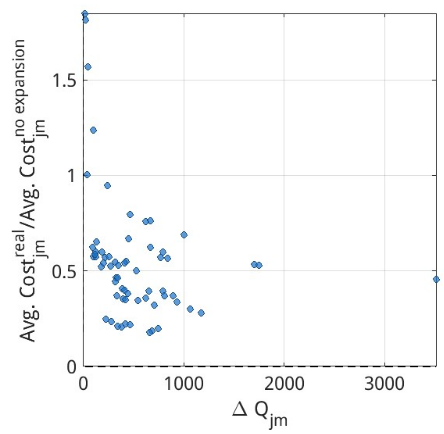
(a) Trend of Average Variable Costs (Relative to No Scope or Density Economies)



(b) A Landlord's Scope, Density, and Cost (Invitation Homes)



(c) Trend of Rental Profits per Unit



(d) Counterfactual: Costs w/o Expansion

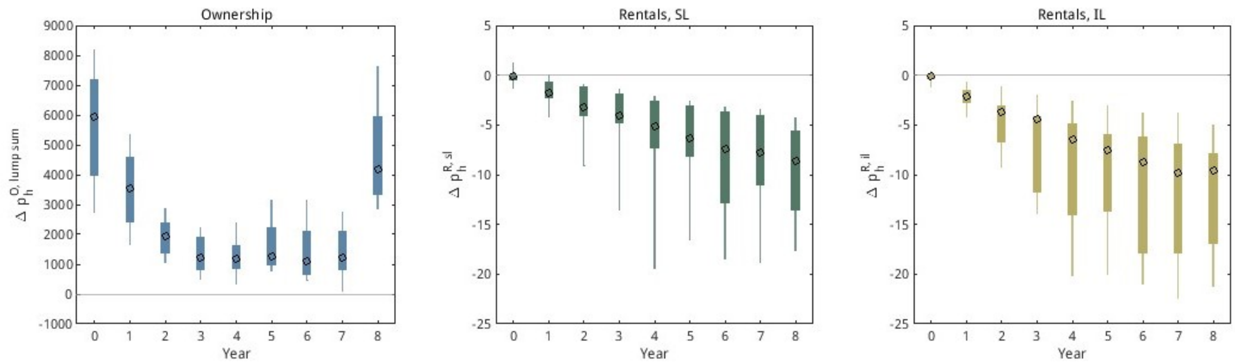
Figure 8: Firm Dynamics in Scope, Density, Cost, and Rental Profit

Notes: In Panel (a) and (c), we plot the trend of average variable costs and per-unit rental profits, for rental homes owned by any of the institutional landlords (black solid), Invitation Homes (red, dashed), and Amherst (blue, dot-dashed). For the industry trends we provide a bandwidth of one standard deviation, visualizing the dispersion of variables of interest across institutional rental units in a given year. In Panel (b), we visualize the within-portfolio evolution of a single landlord's scope and density on a color gradient, representing a continuum of average variable cost levels, relative to the cost level of operating one isolated unit with no scope or density economies. We plot snapshots of three years, Year 0 (red), Year 4 (yellow), and Year 8 (purple), for each the scattered points represent the values of $(Q^{total}, Q^{local})_{hjmt}$ across h in landlord j's stock. In Panel (d), we compare portfolio-average costs at firm-market level w/o Expansion since year 0, and plot changes in fraction against expanded portfolio size from year 0 to year 8.

tion variation is given by

$$CV_{it} = \frac{12}{-\alpha_{d(i)}} \left(\ln \sum_{g} \left(U_{igt}^{\text{With IL}} \right)^{1-\sigma} - \ln \sum_{g} \left(U_{igt}^{\text{No IL}} \right)^{1-\sigma} \right) \tag{41}$$

Figure 9: Price Effects of Institutional Landlords' Expansion



Notes: This figure shows the distribution of type (h) level price differences in each year since 2013, by categories: ownership (blue), small landlords' rentals (green), and institutional landlords' rentals (gold). Boxes show the range of values between 25th to 75th percentiles, with whiskers extending to the 10th and 90th percentiles.

where CV_{it} is measured in year t's dollar. The inclusive value from nest g is given by:

$$U_{igt} = \sum_{h \in g} \exp\left(\frac{\overline{u}_{d(i)ht}}{1-\sigma}\right) \tag{42}$$

where $\overline{u}_{d(i)ht} = \alpha_{d(i)} p_{ht} + X_{ht}\beta_{d(i)} + \xi_{ht}$, denotes the deterministic part of utility that household of demographic $d(i)$ receives from home type h in t.

We separate welfare calculation for households conditional on their choice of renting versus buying in the real world with institutional landlords' expansion. Table 10 presents the comparison in renter shares, size of housing population, and welfare per household conditional on real-world tenure choices. First, with institutional landlords' expansion, the share of renters increases, reaching 92.60% in 2021 with a gap of 1.59% compared to the counterfactual with no expansion. Increase in the share of renters is jointly attributed to two changes in households' choice sets: (i) expanded supply of rentals by institutional landlords, and (ii) increases in home ownership prices driven by institutional landlords' continuing home acquisition. Second, as a result of increasing renter shares in each year's market, the size of housing population, defined as the group of households living in the county with no home ownership in the beginning of a specific year, increases. By 2021, the difference reaches 12,255, or 1.94% of the housing population in the no-expansion counterfactual context. Third, we calculate net gains and losses of consumer welfare measured in each year's dollar terms. Renters (buyers) refer to household choosing to rent (to buy) in the world with institutional landlords' expansion. Consumer welfare calculations in the context without institutional landlords' expansion cover the inclusive values of both ownership options and rental options. For all years in the period of study, on average renters receive net welfare gains from expanded rental choice set and rental price decreases in certain rental types. Compared to renters, households who continue to choose ownership options experience net welfare losses or smaller welfare gains. The loss in buyers' welfare is attributed to the increase in home ownership prices. Finally, we aggregate welfare comparison across years using the monetary measure of 2021 dollar. Over the years, the net welfare gain is \$50.17 per renter year, with 84.04% renters benefiting from the expansion of rental supply and 15.96% renters losing due to diminished access to their preferred affordable ownership options. Remaining buyers incur a net loss of \$31.35 per buyer year from inflated ownership prices.

Table 10: Welfare Changes by Year and Households' Tenure Choice

	2014	2015	2016	2017	2018	2019	2020	2021
Share of Renters (%)								
(with IL expansion)	92.28	91.87	91.54	91.86	92.29	92.01	91.76	92.60
(no IL expansion)	91.40	91.23	91.01	91.20	91.53	91.19	90.99	91.01
(Changes)	0.88	0.64	0.53	0.66	0.76	0.82	0.77	1.58
Number of Households								
(with IL expansion)	539,065	551,753	566,209	571,211	585,472	618,384	623,262	642496
(no IL expansion)	533,808	544,102	557,783	562,688	576,255	608,061	611,687	630,242
(Changes)	5,257	7,651	8,425	8,523	9,216	10,323	11,576	12,255
ΔCS, Renters								
(per household)	19.50	34.14	41.77	52.33	56.04	60.62	66.39	64.94
ΔCS, Buyers								
(per household)	-155.14	-51.38	-10.54	1.17	-12.36	19.88	16.04	-85.53

Notes: This table summarizes the decomposition of aggregated welfare changes by households' tenure choices in the equilibrium allowing institutional landlords' expansion. Calculation of consumer surplus differences for renters involves (i) (with IL expansion) the conditional expectation of maximum utility, conditional on the household's optimal choice being a rental option, and (ii) (no IL expansion) the unconditional expectation of the household's maximum utility.

8 Conclusion

In this paper, we study how dynamically formed cost efficiencies from scope and density drive institutional landlords' expansion and, in turn, alter welfare distribution across heterogeneous households in the single-family home markets.

We first collect and analyze linked datasets of property transactions, rental listings, resident demographics, and institutional ownership in the Atlanta metropolitan area. We document rapid, spatially-clustered expansion of institutional landlords and rich patterns of their strategies in spatial competition and choices of investment timing. In the ownership market, their expansion correlates with higher sale prices, increased transaction volumes, and a reduction in individual home purchases. In the rental market, their investment coincides with expanded total rental supply with no clear price effects.

We build a dynamic equilibrium model of landlord investment with three key features: (i) endogenous housing supply evolution determined by oligopolistic landlords' investment, (ii) endogenous landlord costs varying with portfolio size and density, and (iii) households' substitution within and across buying and renting in an integrated choice set. We estimate the model using firm-property level data from 2013-2022 in the Atlanta metropolitan area. Estimation proceeds in two main parts. First, we estimate the static demand system of housing demand leveraging the exogenous part of variation in housing supply structure across markets. Also we estimate the static supply functions of housing leveraging the demographic shifts from the demand side across markets. Second, built on static estimation results, dynamic estimation further adapts the two-step dynamic estimation framework to the setting of multi-product firms' continuation choice problem. We find that institutional landlords' expansion achieved 60.03% maintenance costs reduction from economies of scope and density. Household total welfare increased with varying effects across renters and buyers. The majority of renters gained from expanded rental supply, while a small fraction of renters, together with most buyers, lost from diminished access to affordable home ownership. Our findings have significant policy implications on regulating institutional landlords' expansion in the single-family home market.

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Supplement to "The Expansion and Dynamic Equilibrium Effects of Institutional Landlords"

A Notation

Table A.1: Description of Notations

Symbol	Description
m	index of geographic market
t	index of year
h	index of house type
j	index of institutional landlord
i	index of household
d	index of demographic type
λ	index of home owner type, $\lambda \in \{oo, sl, il, new\}$
$\mathcal{H}_m$	set of house types in market m
$\mathcal{J}_{mt}$	set of active institutional landlords in market m year t
$\mathrm{P}_{D,mt}$	demographic distribution of housing population in market m year t
Q^{λ}_{hmt}	number of units owned by owner type λ
Q_{jhmt}	number of units owned by branded landlord j
$\xi_{hmt} = (\xi^O, \xi^{R,sl}, \xi^{R,il})_{hmt}$	product level demand shocks
$\epsilon_{ihmt} = (\epsilon^O, \epsilon^{R,sl}, \epsilon^{R,il})_{ihmt}$	idiosyncratic household-product-market-year demand shocks
Φ_{jmt}	flow payoff for landlord j in market mt
avc_{hjmt}	average variable cost for landlord j to operate rentals in house type h
ω_{mt}	real estate employee wage in market m year t
c^I_{jmt}	investment cost for landlord j in market m year t
ν_{hjmt}	house type-landlord specific per-unit investment cost shock
$\mathcal{M}$	common state variables

B Variable Construction

B.1 House characteristics

We use a combination of houses' physical attributes and neighborhood amenities to characterize houses and categorize them into differentiated types.

Bedroom type: We categorize houses into four bedroom types with ≤ 2 bedrooms, 3 bedrooms, 4 bedrooms, and ≥ 5 bedrooms. For properties with missing data in *#bedrooms* in all of its tax records, we predict their number of bedrooms using the distribution of *#bedrooms* from the observed set of houses built on the same land parcel. [I may include some evidence to show the quality of prediction]

Neighborhood walk score: We web-scrape neighborhood walk score from Zillow[27], using a

[27]Zillow's walk score is sourced from Walk Score, a company that provides walkability ratings for neighborhoods

representative sample of SFH properties located across Atlanta neighborhoods. We use the mean value of sampled properties' walk score within a tract to form the tract-level walk score.

Indicators for access to high-quality schools: We web-scrape nearby school information from Zillow[28] using the same sample of properties as described above. We summarize the raw information on a house's nearby schools - school name, category, and scores (from 1 to 10) - into three binary variables: indicator for access to high-quality[29] preschools or elementary schools, indicator for access to high-quality middle schools, and indicator for access to high-quality high schools.

B.2 Monthly cost of homeownership

We define the monthly cost of home ownership (p^O_{hmt}) as the sum of mortgage principal and interest payment, property tax payment, and home insurance[30], that a representative home buyer is expected to pay every month if buying house h in county m in year t:

$$p^O_{hmt} = p^{O,\text{lump sum}}_{hmt} \cdot \left((1-d)\left[r^{\text{mtg}}_t(1+r^{\text{mtg}}_t)^N\right] / \left[(1+r^{\text{mtg}}_t)^N - 1\right] + r^{\text{tax}}_{mt}/12 + r^{\text{insurance}}\right)$$

- Benchmark mortgage: 30-year fixed-rate mortgage with 20% down payment. We collect mortgage rates each year using the level during first week in July
- Property tax rate: the median of empirical tax rates (ratio between tax amount and property's market value) calculated from all SFH properties within the same county and year
- Home insurance premium rate: the median of empirical home insurance rates (ratio between estimated home insurance by Redfin and property sale price) calculated from all SFH properties listed in the MSA. In the Atlanta MSA sample, Redfin data shows little variation in premium rate across SFH properties.

We exclude property transactions with missing prices, inter-family transactions, and multi-property transactions with missing land size in any property transacted, from constructing type-level p^{sale}_{hmt}. For multi-property transactions with all properties' land sizes documented, we allocate the total sale amount to each property based on its proportionate land size.

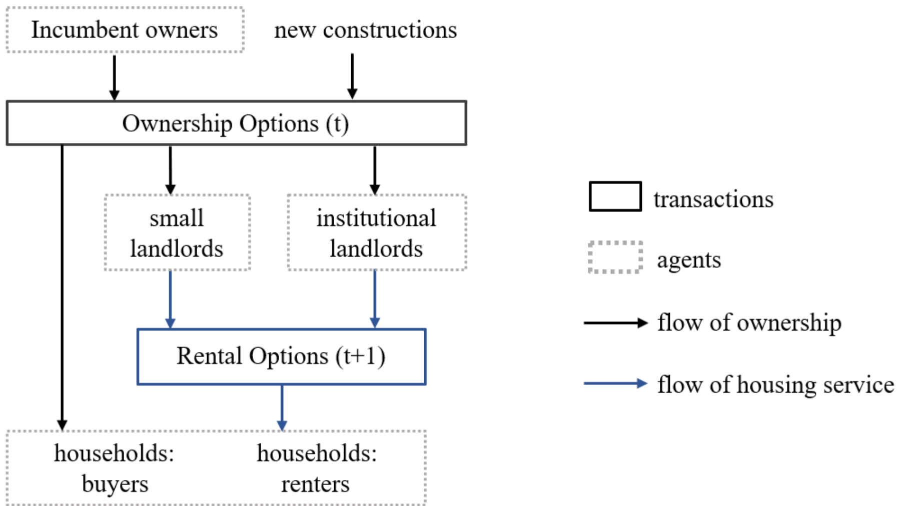
based on factors including the proximity to amenities, the density of intersections, and pedestrian-friendly features. Website: https://www.walkscore.com/

[28]Zillow identifies nearby schools for each property by combining local school district boundary data with the property's location. School score is sourced from GreatSchools, a website providing school ratings and comparison tools based on student growth, college readiness, equity, and test scores for public schools in the U.S. Website: https://www.greatschools.org/

[29]A school is defined as of high quality if its score exceeds the median of all Atlanta schools in the same grade level.

[30]Home insurance is mandated by most lenders if the home is bought with a mortgage.

Figure C.1: Static Model: Integrated Housing Market



C Model Illustration

Figure C.1 illustrates agents, transactions, and flows of homeownership in an integrated housing market with interacting ownership sector and rental sector.

D Counterfactuals

We provide the derivation of compensating variations (CVs) for Equation 41.

Individual i makes optimal choice from a set of options $h \in \mathcal{H}$. We denote the individual-option specific utility shock as v_{ih}, following the Generalized Extreme Value (GEV) distribution. The joint CDF of $\{v_{ih}\}_{h\in\mathcal{H}}$ is

$$F(\mathbf{x}) = \Pr(v_{ih} \leq x_h \ \forall h) = \exp\big[-G\big(e^{-x_1}, \ldots, e^{-x_H}\big)\big] \tag{D-1}$$

where $G(\cdot)$ is the generator function, homogeneous of degree one and increasing in each argument. The plain logit model corresponds to $G(y) = \sum_h y_h$, given individual-option specific shocks independent of each other. In the nested logit model, options are partitioned into nests $g \in \mathcal{G}$ and the generator function is

$$G^{\text{NL}}(y_1, \ldots, y_H) = \sum_{g\in\mathcal{G}} \left(\sum_{h\in g} y_h^{1/(1-\sigma)} \right)^{1-\sigma}, \qquad \sigma \in [0, 1) \tag{D-2}$$

We apply the GEV CDF in Equation D-1 to generator function in D-2 and derive the joint CDF for shocks in nest g $\{v_{ih}\}_{h\in g}$ as

$$F_g\big(\mathbf{x}\big) = \Pr(v_{ih} \leq x_h \ \forall h \in g) = \exp\left\{-\left(\sum_{h\in g} e^{-x_h/(1-\sigma)}\right)^{1-\sigma}\right\} \tag{D-3}$$

We will use the nest-level CDF to derive the distribution of maximum utility within and across nests, en route to the derivation of the expectation of maximum value.

In demand specification, we specify individual i's utility as the sum of two parts: $u_{ih} = \delta_{d(i)h} + v_{ih}$. $\delta_{d(i)h}$ is the deterministic part of utility, specified as $\delta_{d(i)h} = \alpha_{d(i)}p_h + X_h\beta_{d(i)} + \xi_h$. v_{ih} follows the GEV nested logit distribution. We define the nest-level maximum utility as random variable

$$M_{ig} := \max_{h\in g}\{\delta_{d(i)h} + v_{ih}\} \tag{D-4}$$

The CDF of M_{ig}, $\Pr(M_{ig} \leq z)$ is equivalent to the joint probability of event, $\delta_{d(i)h} + v_{ih} \leq z$ holds for all $h \in g$,

$$\begin{aligned}
\Pr(M_{ig} \leq z) &= \Pr(v_{ih} \leq z - \delta_{d(i)h} \ \forall h \in g) \\
&= F_g\big((z - \delta_{d(i)h})_{h\in g}\big) \\
&= \exp\left\{-e^{-z}\left(\sum_{h\in g} e^{\delta_{d(i)h}/(1-\sigma)}\right)^{1-\sigma}\right\}
\end{aligned} \tag{D-5}$$

The second equality is derived using Equation D-3, replacing $x_h = z - \delta_{ih}$. The CDF of M_{ig} shows that M_{ig} is another GEV distributed variable of location $\ln A_{ig}$,

$$A_{ig} := \left(\sum_{h\in g} e^{\delta_{d(i)h}/(1-\sigma)}\right)^{1-\sigma} \tag{D-6}$$

therefore $\gamma^{\text{Euler}} + \ln A_{ig}$ represents the expected maximum utility from nest g.

By definition, the CDF of global maximum is equivalent to the joint CDF of nest-level maximum variables. Given shocks independent across nests, the nest-level maximum $\{M_{ig}\}_{g\in\mathcal{G}}$ are independent across g,

$$\begin{aligned}
\Pr\Big(\max_h(\delta_{d(i)h} + v_{ih}) \leq z\Big) &= \Pr(v_{ih} \leq z - \delta_{d(i)h}\ \forall h \in g) \\
&= \prod_{g \in \mathcal{G}} \Pr(M_{ig} \leq z) \\
&= \exp\left\{ -e^{-z} \sum_{g \in \mathcal{G}} A_{ig} \right\} \qquad \text{(D-7)}
\end{aligned}$$

The second equality holds given shocks distributed independently across nests. The third equality is derived using the CDF of M_{ig} in Equation D-5. The CDF of global maximum shows that the global maximum is another GEV distributed variable of location $\ln B_i$,

$$B_i := \sum_{g \in \mathcal{G}} A_{ig} = \sum_g \left(\sum_{h \in g} e^{\delta_{d(i)h}/(1-\sigma)} \right)^{1-\sigma}. \qquad \text{(D-8)}$$

We then obtain the expectation of maximum utility from the whole set of options $h \in \mathcal{H}$,

$$\mathbb{E}\Big[\max_h u_{ih}\Big] = \gamma^{\text{Euler}} + \ln B_i = \gamma^{\text{Euler}} + \ln \left[\sum_g \left(\sum_{h \in g} e^{\delta_{d(i)h}/(1-\sigma)} \right)^{1-\sigma} \right] \qquad \text{(D-9)}$$

We then derive the unconditional compensating variation by comparing the annual expected maximum utilities for individual i in two scenarios {With IL, No IL}, in monetary terms.

$$CV_i = \frac{12}{-\alpha_{d(i)}} \left(\mathbb{E}\Big[\max_h u_{ih}^{\text{With IL}}\Big] - \mathbb{E}\Big[\max_h u_{ih}^{\text{No IL}}\Big] \right) \qquad \text{(D-10)}$$

E Tables and Figures

Table E.1: Summary of Institutional Landlords and Subsidiaries Cleaning

Brand Name	Code	Years in Operation	Acquired by	No. Subsidiaries Identified
HavenBrook Partners	HB	2012 - 2018	FYR	7
Front Yard Residential	FYR	2012 - 2020	PR	35
Progress Residential	PR	2012 - present	-	132
Starwood Waypoint Homes	SFR	2012 - 2017	INVH	107
Invitation Homes	INVH	2012 - present	-	67
Silver Bay Realty	SBY	2012 - 2017	TAH	15
Tricon American Homes	TAH	2012 - present	-	64
First Key Homes	CCM	2015 - present	-	59
American Residential Properties	ARPI	2008 - 2015	AMH	7
American Homes 4 Rent	AMH	2012 - present	-	69
Amherst Residential	AMHST	2012 - present	-	155

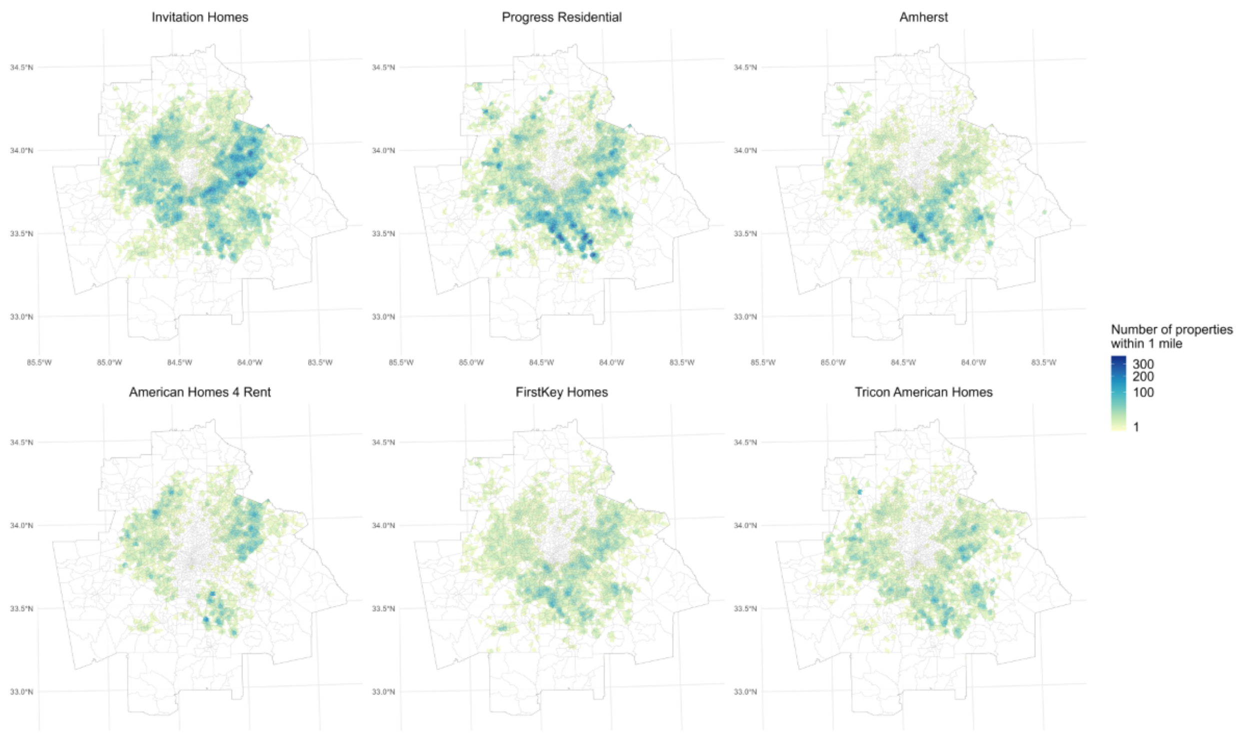
Notes: We only include subsidiaries that participated in Atlanta MSA's single-family house market. Subsidiaries added via M&As are not counted into the acquirer's No. Subsidiaries directly. The same subsidiary can be counted multiple times if the spelling of its name as a buyer is inconsistent across transaction records.

Table E.2: Summary of Demographics and Housing Costs, Atlanta MSA 2022

Markets	Mean HH Income ($)	Mean Age	Bachelor's Share (%)	Mean Children	White non-Hispanic(%)	Black (%)	White Hispanic(%)	Asian (%)	Mean Owner Cost ($)	Mean Rent (SFH, $)	Mean Rent (non-SFH, $)
Barrow	64,981	44.3	24.21	0.96	67.07	10.26	13.10	1.11	1,592	1,150	737
Bartow	81,710	46.5	23.27	1.01	60.33	19.53	14.83	0.00	1,482	921	960
Carroll	64,829	42.2	30.02	0.73	55.29	24.82	9.18	0.47	1,279	911	923
Cherokee	89,180	45.5	48.73	0.90	63.14	7.92	19.74	1.75	1,875	1,524	1,481
Clayton	62,151	44.4	23.85	0.89	4.85	78.81	10.55	1.07	1,483	1,157	1,136
Cobb	85,045	41.8	49.27	0.61	33.29	40.93	13.57	3.06	2,028	1,493	1,422
Coweta	77,949	47.1	39.82	0.77	45.61	35.37	12.14	0.00	2,361	1,216	1,076
DeKalb	78,961	43.7	48.31	0.64	23.10	52.25	10.66	5.51	1,867	1,517	1,416
Douglas	78,727	41.7	36.14	0.93	19.37	64.07	8.90	0.25	1,425	1,293	1,274
Fayette	90,330	49.6	62.61	1.21	39.81	34.14	14.87	2.38	1,987	1,712	1,670
Forsyth	122,578	47.6	64.86	1.01	58.73	9.73	6.51	20.75	2,167	1,682	1,462
Fulton (North)	116,158	43.9	71.31	0.50	41.71	17.60	16.15	13.79	2,849	2,068	1,709
Fulton (South)	62,522	45.6	30.42	0.91	5.36	80.36	5.81	0.13	1,472	1,285	1,090
Gwinnett	79,379	42.6	38.37	0.95	19.08	41.40	24.84	8.09	1,956	1,583	1,375
Henry	79,126	43.7	33.79	1.12	17.39	64.97	8.82	1.11	1,766	1,383	1,311
Newton	76,640	46.5	27.90	0.92	26.88	55.71	8.35	1.93	1,692	1,203	1,131
Paulding	76,007	43.5	25.70	0.93	40.93	40.33	4.10	0.99	1,455	1,171	1,158
Rockdale	76,756	46.5	27.96	0.92	26.91	55.66	8.35	1.95	1,691	1,203	1,131
Walton	73,525	47.0	19.37	0.91	57.19	26.28	3.60	0.84	1,590	1,169	779
Atlanta City	83,145	41.3	55.54	0.31	30.87	49.26	5.39	5.40	2,812	1,424	1,501
Total	83,913	44.8	39.76	0.89	37.94	39.31	11.85	3.51	1,855	1,356	1,252

Notes: We summarize demographics for households who enter housing market with no homeownership in 2022. Incumbent homeowners are excluded from the summary. We report monthly housing costs by tenure types and exclude utility payments from calculation. Data Source: American Community Survey Public Use Microdata Sample (PUMS).

Figure E.1: Rental Portfolio Density of Six Institutional Landlords, Atlanta 2022



Notes: We measure the local density of a landlord's rental portfolio using the number of SFH units operated by this landlord located within 1 mile of the point of evaluation. We visualize the densities evaluated at census block centroids. By 2022, all six institutional landlords have achieved substantial levels of portfolio density with differentiated target locations.

Table E.3: First Stage Regressions: IVs for Static Supply Estimation

	$\log(p^{O,\text{lump sum}})$	$\log(p^{O,\text{lump sum}}/p^{R-sl})$
(Intercept)	5.901	-2.110
	(0.221)	(0.228)
share_income_50to100k	1.518	0.465
	(0.076)	(0.078)
share_income_100to150k	2.230	0.853
	(0.119)	(0.124)
share_income_150to200k	3.323	0.614
	(0.222)	(0.230)
share_income_200kup	2.940	1.082
	(0.216)	(0.226)
share_race_white	-1.737	-0.185
	(0.167)	(0.173)
share_race_black	-1.129	-0.284
	(0.180)	(0.186)
share_race_asian	-1.134	-0.100
	(0.280)	(0.290)
share_race_hispanic	-0.569	-0.020
	(0.223)	(0.232)
share_educ_bachelor	0.203	-0.187
	(0.082)	(0.085)
share_age_25to35	-0.885	-0.000
	(0.181)	(0.188)
share_age_35to45	-1.506	-0.234
	(0.190)	(0.198)
share_age_45to55	-0.765	-0.112
	(0.197)	(0.205)
share_age_55up	0.020	0.010
	(0.187)	(0.195)
FEs: home type	X	X
Multiple R^2	0.886	0.640
Adjusted R^2	0.870	0.591
F-statistic	58.85	13.04
Obs.	6,899	5,726

Notes: This table summarizes the first-stage regression results for demographics instruments used in estimation of static supply functions. We measure the total ownership price of houses, $p^{O,\text{lump sum}}$ in \$1,000, not including property taxes, mortgage interests, or insurances. We measure the rental prices of small landlords, p^{R-sl} using the monthly rents in \$.

Table E.4: Correlation between Demographics and Housing Characteristics

	Monthly cost ($1,000)	Three-bedroom	Four-bedroom	Five-bedroom	Indicator: ownership	Indicator: SFH
log(income)	0.325	-0.062	0.116	0.142	–	0.142
Income group: $50k-$100k	–	–	–	–	-0.039	–
Income group: $100k-$150k	–	–	–	–	0.147	–
Income group: $150k-$200k	–	–	–	–	0.175	–
Income group: $200k+	–	–	–	–	0.258	–
Number of child: 1-2	0.062	0.019	0.072	0.057	0.058	0.196
Number of child: > 2	0.016	-0.060	0.106	0.113	-0.057	0.143
Age: 25-35	-0.023	–	–	–	-0.013	-0.103
Age: 35-45	0.051	–	–	–	-0.051	0.080
Age: 45-55	0.047	–	–	–	0.029	0.098
Age: 55+	-0.056	–	–	–	0.066	0.018
Bachelor's Degree	0.389	–	–	–	0.277	–
Race: White, non Hispanic	0.124	–	–	–	0.142	–
Race: Black	-0.174	–	–	–	-0.156	–
Race: White, Hispanic	-0.037	–	–	–	-0.055	–
Race: Asian	0.114	–	–	–	0.089	–

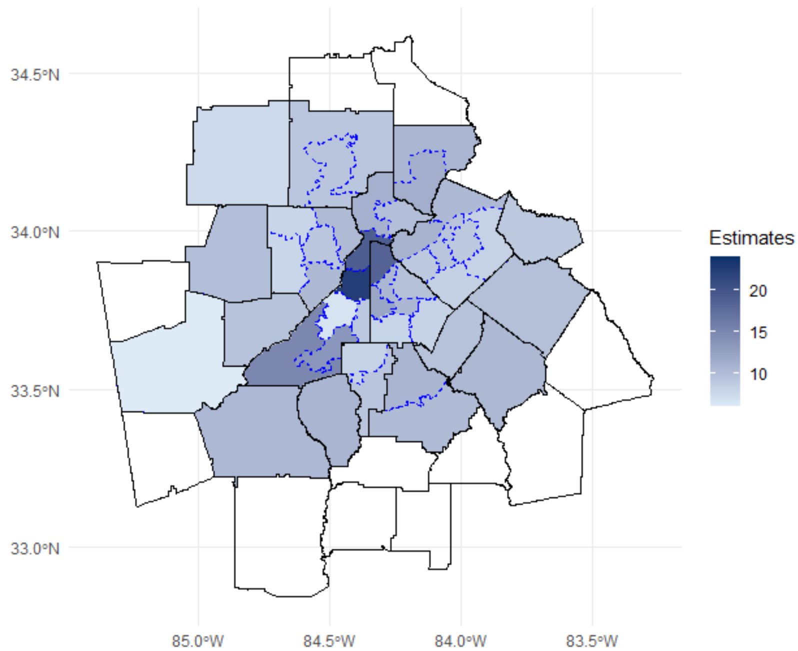
Notes: The table presents correlation between household demographics and housing characteristics chosen by the household. Data source: Data Source: American Community Survey Public Use Microdata Sample (PUMS)

Table E.5: Frequency of Institutional Landlords' Net Purchases (per Year) in House Types

Firms	**Types ever invested**									**Never invested**
	<-5	**-5 - -1**	**0**	**1-5**	**6-10**	**11-15**	**16-20**	**21-25**	**>25**	**0**
Invitation Homes	52	373	2521	1109	263	105	57	41	114	2493
Progress Residential	0	60	1958	1111	241	93	55	24	67	3519
American Homes 4 Rent	4	182	1583	736	128	52	17	6	10	4410
Amherst	2	33	1861	999	164	68	32	23	58	3888
Tricon American Homes	5	71	1796	629	122	42	23	13	26	4401
FirstKey Homes	0	18	2476	928	183	54	37	19	29	3384
Starwood Waypoint Homes	16	308	1122	450	118	53	33	11	44	1805
Front Yard Residential	2	67	1711	512	69	28	14	10	27	3896
HavenBrook	46	171	600	247	41	11	2	3	7	3624
Silver Bay	4	104	685	359	48	16	10	0	9	2725
American Residential Properties	1	11	401	201	33	13	3	2	4	1707

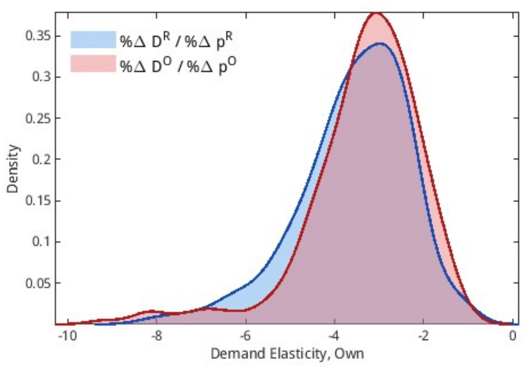
Notes: This table summarizes the distribution of a_{jhmt} in the data by firms. We group the investment choices—the number of home units bought by firm j in type h in market mt—into value ranges and report the value range frequencies in the table. Two main takeaways motivate our modeling choices. First, choices take values over a wide range, which justifies modeling the investment choice as a continuous variable. Second, small-scale disinvestments at the firm–home-type level are observed in many cases. We therefore allow choice variables to take negative values.

Figure E.2: Demand Estimates: Single-family Home by PUMA Fixed Effects

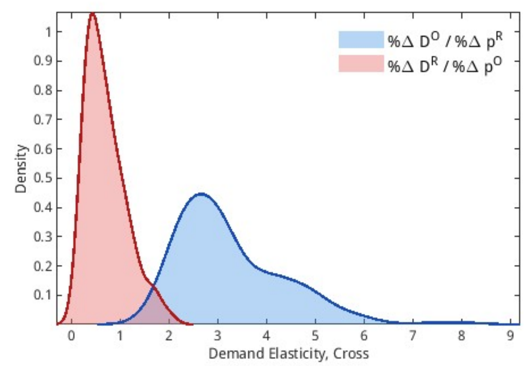


Notes: This figure illustrates the coefficient estimates of single-family home indicator and regional fixed effects in the utility function. Solid boundaries represent counties, and dashed boundaries represent Public Use Microdata Areas (PUMAs).

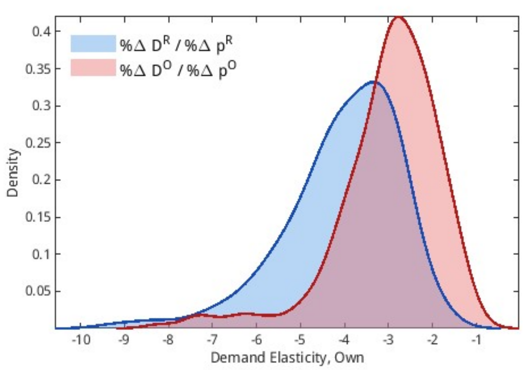
Figure E.3: Demand Elasticities: Own, Cross, and with(out) Equal Supply



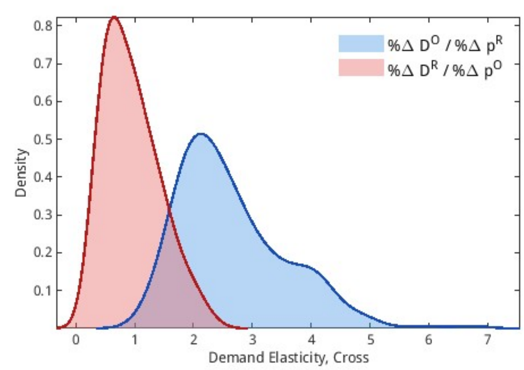
(a) Own Price Elasticities (Supply: Data)



(b) Cross Price Elasticities (Supply: Data)



(c) Own Price Elasticities (Supply: Adjusted)



(d) Cross Price Elasticities (Supply: Adjusted)

Notes: This figure shows the demand elasticities (own and cross), under supply structure fixed at the data level (Panel (a), (b)) or under supply structure adjusted to allow equal total supply in ownership SFH options and rental SFH options (Panel (c), (d)). The adjustment is meant to isolate the effects of supply structure and to show implications of preference parameters and their heterogeneity across demographics only.