The Impact of Institutional Owners on Housing Markets*

Caitlin S. Gorback, McCombs School of Business, UT-Austin†
Franklin Qian, UNC Kenan-Flagler Business School‡
Zipei Zhu, UNC Kenan-Flagler Business School§

April 2025

Abstract

Since the Great Recession, Long-Term Rental (LTR) companies, including single-family rental and private equity firms, have reshaped the U.S. investor landscape. Using housing deeds data from 2010 to 2022, we show that LTRs outpaced other investors, and concentrate geographically. We develop an instrument that predicts LTR market share based on local product preferences and decreasing management costs. A one-standard-deviation increase in LTR share raises house prices by 1.58 p.p., lowers homeownership by 0.53 p.p., and does not affect rents. These averages mask significant temporal heterogeneity. LTRs contribute to a 0.32% national homeownership decline by acquiring homes from owners and speculators.

*We thank the seminar participants at Cavalcade, Baruch College (Zicklin), Federal Reserve Board of Governors, Federal Reserve Bank of Chicago, University of Colorado Boulder (Leeds), University of Southern California (Marshall), Stanford SITE for Housing and Urban Economics, Cornell Real Estate Symposium, SF Fed-UCLA conference on housing, financial markets, and monetary policy, ASSA-AREUEA, UEA North American Meeting (Georgetown), Pre-WFA Summer Real Estate Research Symposium, 2nd Annual Conference on Market-Based Solutions for Reducing Wealth Inequality, CICF, ITAM Finance Conference, and RERI Annual Conference for their valuable comments. We are grateful for the feedback provided by our discussants Jacques Gordon, Yuecheng Jia, Antoine Levy, Vrinda Mittal, Michael Reher, and Tingyu Zhou as well as Steven Billings, Rebecca Diamond, Jack Favilukis, Edward Glaeser, Joseph Gyourko, Lara Loewenstein, Tim McQuade, Sam Rosen, Martin Schneider, Alexei Tschistyi, Sheridan Titman, and Anthony Lee Zhang for their helpful comments. We thank the Real Estate Research Institute for their generous funding of this project. We thank our dedicated RAs for their excellent research assistance.

†Email: caitlin.gorback@mccombs.utexas.edu
‡Email: franklin_qian@kenan-flagler.unc.edu
§Email: Zipei_Zhu@kenan-flagler.unc.edu

Introduction

Small landlords have always provided single- and multi-family units for rent. However, larger institutional investors entered the residential housing market during the Great Recession when firms such as Blackstone first bought up thousands of single-family homes. The news media and policymakers have characterized institutional landlords as villainous monopolists, driving up prices and rents, and inhibiting households' paths to homeownership. This characterization stands in contrast to their small market shares, at 0.43% of the national single-family and townhome housing stock, suggesting there may be other drivers of these market outcomes. Furthermore, there are potential benefits from providing much-needed space through rental transitions. We aim to shed light on this discrepancy, noting that the role of institutional landlords remains poorly understood.

We address this gap by systematically tracking the growth of single-family, long-term rental companies (LTRs), and compiling a comprehensive dataset of their transactions and ownership from 2010 to 2022. This allows us to measure how LTRs differ from traditional landlords in their housing products and potential tenant preferences. Combined with the variation in falling management costs, we use these differential preferences over the built environment to develop a novel instrumental variable strategy. This design utilizes quasi-experimental variation in LTR neighborhood entry. We then estimate the causal impact of increases in LTRs' presence on local housing markets' prices, rents, and homeownership. On average, we find that prices rise, rents do not change, and homeownership falls, but these averages mask significant heterogeneity: rents initially fell as the supply of single-family rentals increased, and it wasn't until the COVID-19 era that neighborhoods saw meaningful price and rent increases. To identify the mechanisms driving these results, we study the relative impact of LTRs' buying from different types of sellers, including owner-occupants, speculators, or other landlords. When buying more from owner-occupants or speculators, rents fall more, consistent with supply expansion. Transactions that reduce the homeownership rate lead to price declines, suggesting negative spillovers of growing rental communities onto house prices.

To build the LTRs' portfolios, we start by using detailed housing transaction data to construct a novel data set of ownership spells. As large investors often purchase real estate under subsidiary legal entities, we scrape SEC 10k filings, comb through public company records such as Open Corporates, track industry reports, and utilize AI tools to aggregate portfolios up to the parent company level. This yields the annual portfolio of real estate holdings for each owner-occupant, small landlord (SLL), or LTR, among other investor types. In particular, by aggregating portfolios by investor type, we see that the LTRs disproportionately grew between 2010 and 2022, with negligible presence in 2010, but owning nearly 3% of the single-family rental stock by 2022.

Next, we aggregate investor holdings for SLLs and LTRs within a Census Tract and year to measure each group's market share. The 99^{th} percentile Tract saw LTR presence grow from less than 1% of single-family units to more than 9%, while the 75^{th} percentile only grew from 0% to 1%, highlighting that these firms concentrate their holdings to achieve local scale. The rise in investor share is higher in neighborhoods with newer, mid-size, single-family units, in particular those with low vacancies and high minority shares. These findings support the broader media narrative that these firms target the single-family housing stock preferentially relative to smaller, traditional landlords, potentially expanding the rental supply of single-family homes. Additionally, due to the demographics of these targeted areas, our findings are consistent with the potential for gentrification.

We wish to measure the impact of rising LTR shares on Tract-level house prices, rents, and homeownership; however, these variables may also encourage entry, leading to a reverse causality problem that hinders identification. Additionally, we caveat that our LTR share metric is likely underestimated, as many private holdings of real estate are not easily traceable back to parent companies. Finally, there are many amenities and local market characteristics unobservable to the econometrician, introducing omitted variable bias. To overcome these endogeneity concerns, we build a shift-share instrument leveraging cross-sectional variation in the built environment and temporal variation in remote management costs.

For cross-sectional variation, we exploit the pre-existing built environment in a location, which provides exogenous variation in the probability that LTRs enter. We construct a "Suitability Index" based on how amenable the 1990 product mix is to those characteristics revealed as being correlated with LTR entry between 2010–2022, controlling for the characteristics that other landlord types also prefer (i.e. *all* landlords prefer low unemployment rates, so we isolate and exploit *only* the LTR-specific deviation). This yields the differential suitability particular to LTR entry relative to other landlords. Noting that LTRs may also respond to endogenous socioeconomic and demographic factors, such as employment rates or income, we orthogonalize the index to those factors. The relevance condition requires that LTRs differentially favor certain products, while the exclusion restriction requires that ex-ante characteristics would not impact housing outcomes differently two decades later, except through their relative suitability to LTRs. For our temporal variation, we track venture capital funds flowing into online property management (OPM) software startups; this provides a proxy for the declining cost of remotely managing a disaggregated real estate portfolio. We further interact national funding flows with potential customer base, as proxied by non-local property management firms.

Our identification strategy follows a two-stage least squares methodology in which we instrument LTRs' local market share with the interaction between falling management costs and local suitability. We then regress housing market outcomes on the instrumented LTR market shares to analyze how LTRs impact Tract-level house prices and rents. We estimate our specification in changes-on-changes, over the period 2010-2022. This design is consistent with the canonical examples in Bartik (1991) and Blanchard and Katz (1992), which allows the baseline shares (here, our Suitability Index) to be correlated with prices in *levels* while assuming the baseline shares are exogenous to *changes* in the second stage outcome variable (Goldsmith-Pinkham et al., 2020). While we use off-the-shelf data for house prices and homeownership rates, we build a new Tract-level single-family rental index. We do so for two reasons: one, to avoid the measurement error associated with an index blending multiple unit types, and two, to directly control for the changing characteristic composition and quality in the single-family rental stock. Finally, we include county-by-year fixed effects, to allow for LTRs' choice of broad market, leveraging the remaining cross-Tract variation.

In the first stage, we find that a one standard deviation increase in the annual change in our instrument implies a 0.11 standard deviation increase in the annual change in LTR market share. Our first-stage F-statistic ranges from 24 to 45 across different regression samples, indicating a strong first stage. In the second stage, we find that a one standard deviation increase in instrumented LTR share causes a 1.58 p.p. increase in house prices. In contrast, for our rent sample, a one standard deviation increase in instrumented LTR share causes only a 0.80 p.p. increase in rents between 2010 and 2022, which is not statistically significant. The point estimate remains insignificant and flips sign when focusing on top decile Tracts in LTR presence as of 2022, suggesting that the expansion of rental supply due to LTR entry likely puts downward pressure on rents. Finally, we find that LTR share growth significantly impacts homeownership rates during the last decade. A one standard deviation increase in LTR share leads to a 0.53 p.p. decline in the homeownership rate, highlighting the changing dynamics of housing tenure driven by the expansion of LTR companies.

One may be concerned that the instrument cannot account for other concurrent trends in housing markets, such as gentrification, urbanization, or recovery from the Great Recession. First, our county-by-year fixed effects control for broad, market-level demand shocks. Second, for within-county concerns, we orthogonalize the cross-sectional variation in our instrument with respect to socioeconomic and demographic neighborhood characteristics. As such, we utilize variation independent of these underlying trends in our analysis. We further explore whether concurrent demand shocks are correlated with our underlying suitability index. For example, there may be a shift in housing preferences among the broader population in alignment with those preferred by LTRs. To test this, we examine the long-run differences in outcomes across locations with similar suitability, but which differ in their LTR entry status. Should our instrument fail the exclusion restriction, we would expect similar trends in outcomes across both samples. Instead, we find economically and statistically different relationships between suitability and our outcomes, *conditional* on entry. This lends credence to our exclusion restriction assumption: our instrument impacts prices, rents, and homeownership directly through changes in LTR market share. Finally, in robustness checks, we include controls for the magnitude of the price increase leading up to the Great Recession, as well as the size of the price collapse, to address concerns that prices and rents rose in these markets solely due to recovery from the bust, rather than LTR interest. We find similar price, rent, and homeownership impacts as our baseline estimates.

These findings exhibit significant heterogeneity when we break them down by the LTR industry's different eras. During its birth, from 2010 to 2014, prices remained constant, while rents and homeownership declined. This is consistent with investors supporting prices that would otherwise be in free-fall coming out of the Great Recession, as in Lambie-Hanson et al. (2022). As investors purchased foreclosed homes, homeownership rates declined, while rents fell due to the increased rental supply. During the growth phase, from 2015 to 2019, characterized by the rise of cheap financing via the offering of debt securities backed by rental incomes, prices began to fall, while homeownership and rents stabilized, relative to the earlier period. Finally, during the COVID-19 era in which demand for space increased, prices and rents rose with LTR market share, while homeownership fell, potentially as sophisticated landlords were more likely to use dynamic rent repricing (Calder-Wang and Kim, 2023).

Having identified changes in prices, rents, and homeownership, we examine the underlying mechanisms driving our findings. While we remain model agnostic, we can utilize the type of ownership transition to shed light on potential mechanisms. In particular, we study landlord professionalization, reallocation of housing from owners to renters, LTR concentration, and spillovers induced by rising rental market shares. For example, to study the professionalization channel, we study Tracts with the most transitions from SLLs to LTRs. We find that prices and rents fall more in locations with the most housing reallocated from owner-occupants or speculators to LTRs, suggesting that supply expansion drives baseline rent decreases. The subsequent increase in the renter share depresses prices, suggesting negative price spillovers, potentially due to poor maintenance (Billings and Soliman, 2023) or preferences for the changing demographic mix (Diamond and McQuade, 2019).

Related Literature

The roles of various types of investors in housing markets have garnered much attention since the Great Recession. Out-of-town buyers (Chinco and Mayer, 2016; Badarinza and Ramadorai, 2018; Favilukis and van Nieuwerburgh, 2021; Cvijanoviċ and Spaenjers, 2021), speculators (DeFusco et al., 2022; Bayer et al., 2021, 2020; Mian and Sufi, 2022), and iBuyers (Buchak et al., 2022) have all played significant roles leading up to the Great Recession and during the recovery. In this paper, we focus on the rise of institutional investors providing long-term rentals (LTRs), documented by Goodman et al. (2023) as having taken off since 2012. We contribute to this literature by highlighting the role of a new class of investors that arose after the Great Recession: the LTR companies and, more broadly, the role of private equity as landlords. Additionally, many of these papers, i.e. Bayer et al. (2020) and Chinco and Mayer (2016) utilize changes in the transaction flow to identify price impacts, rather than the share of the stock. Since we observe holdings as well as transactions, we can directly study changes in homeownership composition in addition to prices and rents.

A growing literature studying these investors documents their role in supporting prices in the single-family housing market (Mills et al., 2022; Lambie-Hanson et al., 2022; Bayer et al., 2021) These investors prop up prices in declining locations, leading to returns (Allen et al., 2018; Demers and Eisfeldt, 2021; Harrison et al., 2024). We document that the new class of LTR investors not only contribute large and highly concentrated transactions but seem to select markets with low vacancies and healthy labor markets, eyeing consistent rents to support rental profits, even before realizing returns when they sell their portfolios. More recent work has analyzed investors' impact on local affordability. (Austin, 2022; Elster et al., 2021; Garriga et al., 2023; Gurun et al., 2022; Rutherford et al., 2023). While much of this literature leverages mergers to identify the impact of LTRs' market concentration on local rents, we predict entry into a location based on preexisting product characteristics more suitable for the LTR cohort of firms. This allows us to look at a much more geographically diverse set of communities and mitigates concerns of endogenous mergers targeting market concentration in gentrifying areas.

Concurrent work from Barbieri and Dobbels (2024); Chang (2024); Coven (2024); Hanson (2024) also study the impacts of LTRs on local housing markets. All authors find that prices rise, but Barbieri and Dobbels (2024), Chang (2024), and Coven (2024) find that rents fall, while Hanson (2024) finds that rents rise. We contribute by providing the broadest setting, studying the national industry from 2010-2022, and manually collecting data on 58 different LTRs, both publicly listed and private equity driven.[1] This allows us to study different samples and potentially reconcile these conflicting findings; for example, we find that rents rose on average, but fell in locations with high transitions from owner-occupancy, as in Atlanta and Charlotte. Complementing these structural papers, we take a data-driven approach and provide model-agnostic results utilizing a novel instrument, though we admit that our treatment effect is limited to those complying locations, as in standard IV practice.

1 Institutional Background

While there has always been a single-family rental market in the USA, institutional involvement in earnest began with the housing collapse of 2007-2009. Blackstone, the asset manager, had first dabbled in residential ownership with the purchase of a few apartment

[1] Barbieri and Dobbels (2024) uses a search model in Atlanta between 2023 and 2024; Chang (2024) uses data from four southern U.S. states since 2012, identifies 23 LTRs, and estimates a quantitative spatial equilibrium model; Coven (2024) uses a demand-based asset pricing model calibrated to Georgia (the largest LTR market), tracks 7 LTRs, and national data from 2015-2019 and 2021; and Hanson (2024) uses a portfolio choice model and instrumented expected excess returns to provide variation in LTR entry in ~ 600 national submarkets, following 10 firms.

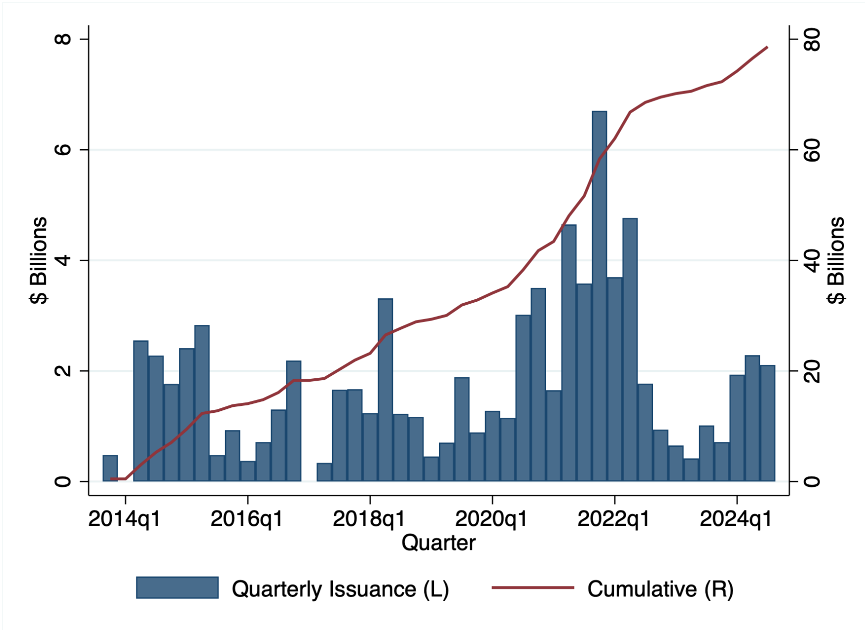
buildings after the Savings & Loan Crisis of the early 1990s but did not see a route to scale in that era (Christophers, 2023). Nearly 20 years later, a series of developments in the available housing stock, financing, and technology made achieving scale feasible.

Blackstone realized that making meaningful profits in residential real estate required a large portfolio, something difficult to put together in the illiquid single-family housing market. This changed with the Great Recession when thousands of households lost their homes. Counties auctioned hundreds of foreclosed homes per week, and investors accumulated portfolios of single-family homes overnight. Institutional investors could easily outbid potential owner occupants or small landlords, with their access to large cash reserves, secured by taking out cheap debt as credit contracted for small borrowers (Christophers, 2023).

Originally, this move into the single-family residential market looked like a capital gains play, in which institutional investors would buy houses cheap and sell them for a large return upon recovery in demand. Invitation Homes, one of the largest LTRs, recognized that operations also yielded profits. In November 2013, Invitation Homes offered the first public debt securities backed by single-family rental income, kicking off a popular funding strategy, as shown in Figure 1. By 2024, the industry had issued nearly \$80 billion. Pretium Partners (which owns Front Yard Residential and Progress Residential), Invitation Homes (spun off from Blackstone in 2017), Cerberus Capital Management (owner of FirstKey Homes), Amherst Holdings, and Tricon Residential (acquired by Blackstone in 2023) lead the way with \$21.5 billion, \$11 billion, \$8.6 billion, \$7.2 billion, and \$7 billion, in issuance, respectively, but 16 other firms have also offered these securities. This activity improved the financing position of LTRs relative to other potential buyers, such as small landlords or owner occupants, and was cheaper than traditional debt (Christophers, 2023). These securitizations boomed during the COVID-19 era, during which households flocked to less dense areas, favoring single-family homes with yards and space for home offices over their dense urban apartments (Gupta et al., 2023; Davis et al., 2024).

After securing cheap financing, LTRs have managed and operated their portfolios, the largest of which holds 80,000 homes. Fred Tuomi, current Vice Chairman of Real Estate at Pretium Partners, formerly of Invitation Homes and Starwood Waypoint, two other major LTRs, noted that investors typically balked at managing geographically dispersed portfolios, "back in the old days... 15 years ago we thought you couldn't scale single-family rental (SFR) management... the individual home is the challenge that scared people a lot of

Figure 1: Issuance Backed by Rental Income



Notes: This figure plots the quarterly and cumulative issuance of public debt offerings securitized by rental income streams. Pulled from Bloomberg, aggregations authors' own.

people."[2] For this reason, over 67% of rental units are in multi-family buildings, according to the 2020 Census. The concurrent rise of online property management platforms (OPMs) enabled decentralized management. These platforms allow for remote tours, connection with smart appliances to monitor usage and outages, filing and resolving maintenance requests, scheduling deliveries, and lease applications, among other operations tasks.

These management costs fall with scale. When discussing the benefits of buying clusters of homes, Tuomi notes, "the vendors like it, you get more efficient pricing." Indeed, in Section 4, we show that the marginal cost of managing a unit using OPM falls significantly with scale: Buildium's management platform costs ∼$60/month for investors with 1 property, but this per-unit cost falls below $3/month per unit for a portfolio of 100 homes. Importantly, OPM scale interacts with *local* scale, since humans physically need to attend to many management and maintenance tasks. This loops back to increased product availability during the Great Recession. Foreclosures were often regionally clustered due to concurrent labor mar-

[2] "The Merging Worlds of Multifamily & SFR," *The Rent Roll with Jay Parsons.* Dec 12, 2024. Retrieved via https://www.youtube.com/watch?v=zpwqhP6W0gw.

ket downturns. These foreclosures further depressed house prices, leading to more borrowers potentially underwater and foreclosure contagion (Gerardi et al., 2015; Gupta, 2019). This offered a great opportunity for the LTRs: in the past, buying single-family homes was not only illiquid but also spatially fragmented. For the first time, LTRs could sweep up hundreds of homes in a given county in a week. More recently, given the few foreclosures, LTRs have partnered with builders to develop clusters of single-family homes from the ground up.

These innovations in technology and financing enabled LTRs to take advantage of the unique availability of single-family products following the Great Recession, and the contraction in credit conditions for owner-occupants increased demand for rentals, with the homeownership rate falling in 2016 to levels not seen since the 1960s. Combined with record low housing supply in the past decade (Gorback and Keys, 2020), exacerbated by the contraction and concentration in the construction industry (Quintero, 2023), demand for single-family rentals was poised to soar. Figure 2 plots the raw rental share of single-family homes in the US between 2010 and 2022, dividing the sample into Tracts with LTR activity as of 2022 and those without. The overall shape of the curve mirrors the decline in homeownership: single-family rental rates rose between 2010 and 2016 when they peaked. In Census Tracts with LTR entry, the single-family rental rate started lower, as these were more likely to have high rates of homeownership. Over time, as LTRs moved in and transitioned stock from owner occupancy to the rental market, the gap between locations narrowed.

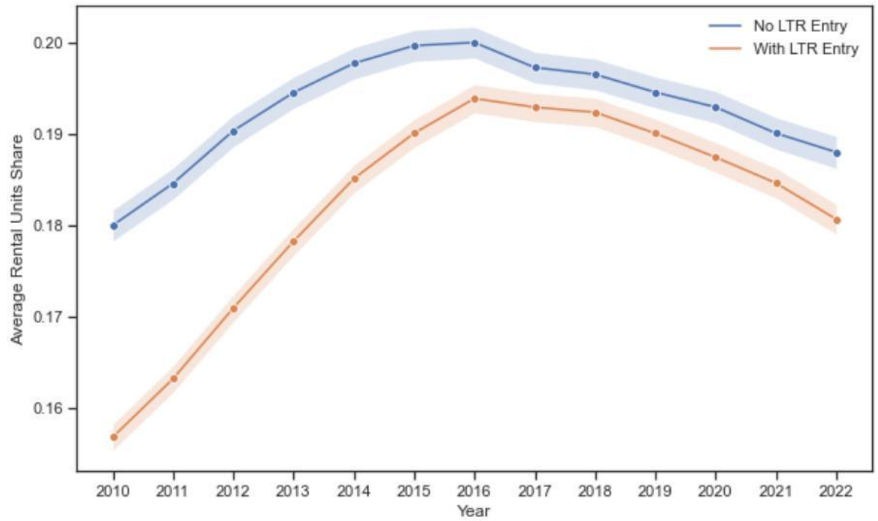
In sum, the marriage of opportunity, technology, and cheap financing enabled LTRs to develop an entirely new industry in single-family rentals over the last decade, one maintained by strong demand due to households' inability to borrow, builders' contraction in new supply, and the rise of remote work leading households to demand more space.

2 Data

Corelogic Deed Records and Tax Assessment: Our core dataset contains 200 million detailed deed records from the early 1980s to October 2022 for more than 2,400 counties in the US.[3] Our sample covers all single-family houses and townhomes, and includes transaction dates, prices, addresses, buyer and seller information, etc. We only include arms-length transactions. We obtain property characteristics from the latest tax assessment updated by

[3]We only keep counties with $\geq$1,000 transaction records in total since first appearance in the data.

Figure 2: Trends in Rental Rates



Notes: This figure shows the raw rental shares in Census Tracts in which LTRs remained active as of 2022 vs. those with no LTR activity. Data from the American Community Survey, 5-year estimates 2010–2022. The sample was restricted to Tracts that existed in all years; new, combined, or Tracts with changing boundaries dropped from the sample to keep constant geographies.

October 2022. We primarily use Deeds data from 2000-2022, but supplement with transactions dating to the mid-to-late 1990s to find early owner names for our ownership panel.

CoreLogic MLS: We obtain historical rental listings from CoreLogic MLS data from 2000 to 2022, including information such as listing date, asking rent, contracted rent, listing agent name, etc. This data became available relatively recently, with minimal other work utilizing it, as far as we are aware.[4] Multiple Listing Services are private platforms, built and maintained by collectives of real estate brokers that allow owners of real estate to list their properties for sale. These platforms incentivize broker cooperation, allowing for deeper real estate markets by pooling listings; buyers thus have access to all local listings on the MLS, even those not represented by their broker or their broker's home office. There are more than 500 MLSs across the U.S., covering markets of varying sizes, and this number changes annually as local MLS merge and form. These MLS platforms form the backbone of many of our familiar online rental listing products, including those on Zillow, Redfin, and Realtor.com, populating multiple website listings automatically through MLS updates. A

[4]Work in progress by Abramson, De Llanos, and Lu use data from Altos Research, which itself is based on MLS listing. Chang (2024) also uses MLS rental listings data.

key benefit of MLS data is its availability over our entire sample period of interest. Another common data source, Zillow's Observed Rent Index (ZORI), begins in 2015, precluding us from studying the birth of the industry through the first years of debt offerings. See Appendix Figure D1 for a comparison of CoreLogic MLS vs. ZORI coverage samples over time.

With this data, we construct a novel single-family rent index. While there are many rent indices publicly available, such as the FHFA's Fair Market Rent (FRM) or Zillow's ZORI, all of these blend multi-family and single-family rental units into one comprehensive index. We construct our own rent index to match our context, limiting the sample to single-family and townhome units. In contrast to work using an MLS single-family repeat-rent specification (Chang, 2024), we choose a hedonic specification, due to the large transfer of units from owner-occupancy to renter-occupancy. A repeat-rent framework would miss the initial rent set after a home transitions from owner-occupancy to the rental market since it requires observing rents for the *same unit* at two points in time. This better controls for the evolving composition of single-family rentals, many of which are larger and newer than prior rentals. A benefit of repeat-rent indices is their ability to control for quality. Instead of the property fixed effect, we utilize a rich set of controls. Below is our hedonic regression specification:

$$\log(R_{i,j,t}) = \sum_{\tau} \beta_{i,\tau}\mathbf{X}_{i,t,\tau} + \alpha_{j,t} + \phi_m + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,j,t}$ is the contracted rent of property i, in Census Tract j, in year t. The vector $\mathbf{X}_{i,t,\tau}$ is a suite of property characteristics where τ indexes each characteristic. $\mathbf{X}_{i,t,\tau}$, includes property age and its square, log of living square footage, log of acreage, bedrooms, bathrooms, number of stories, a dummy for whether it is a new construction, a set of dummies for whether the unit has a garage, cooling, heating, fireplace, pool, and security features. $\alpha_{j,t}$ is a Census Tract-by-year fixed effect, from which we construct our local rent index, and ϕ_m is a month indicator to control for seasonality in housing market cycles.

Federal Housing Finance Agency (FHFA): We use the FHFA's annual Tract level house price index for house prices. The FHFA constructs a weighted, repeat-sales index using all single-family purchases with conventional, conforming mortgages purchased or securitized by one of the Government-Sponsored Enterprises. The data began in the 1970s for most Tracts, and we limit our analysis sample to 2000-2022 in line with our other outcomes.

U.S. Census Bureau: We compile information on property, demographic, and labor market characteristics at the Census tract level for all counties in the U.S. from the American Community Survey (ACS) and the Decennial Census. Additionally, one of our main outcomes, homeownership, comes from this source. We use data from the 1990 and 2000 Decennial Census as well as the five-year aggregates from the 2012 American Community Survey[5].

SEC 10K Fillings: We compile subsidiaries for a list of publicly traded companies, such as REITs, single-family rental companies, or large asset managers. Specifically, we find all subsidiaries for each parent company in each year while a company is public. This maps the many small, legal subsidiaries used to purchase real estate to their parent companies.

OpenCorporates: We observe many entities that purchase large amounts of single-family homes, but which are not obviously tied to a parent company. For example, American Homes 4 Rent does not buy homes as "American Homes 4 Rent." Instead, we find many examples such as "AMH Borrower YEAR-Q# LLC." We search the largest 10,000 investors identified after name harmonization on OpenCorporates.com. This website provides data on corporate entities in a harmonized format, gleaned from state and national business registries. We map the opaque legal entities to their parent companies using OpenCorporates.com's lists of subsidiaries, address matching, or manager/director name matching.

2.1 Constructing Ownership Panels

We use the CoreLogic Deeds database to impute the ownership for every single-family (detached or semi-attached) or townhome property, annually from 2000 to 2022. To do so, we rely on buyer and seller information from historical transactions to back out the ownership of a property over time. Intuitively, we fill in a balanced panel for each property by expanding transactions into ownership spells. For example, we observe that John Smith purchased a newly built home in 2004, and then sold it to Jane Doe in 2013, after which we see no more transactions. We assign John Smith as the home's owner between 2004 and 2013, and Jane Doe between 2013 to 2022. That is, the panel is constructed for a given *property* in each year between 2000 (or the year the home was built) and 2022, with ownership varying over time. The ownership panel is our key novel data set for most analyses. Appendix A.1 gives an example of how we construct the ownership spells.

[5] The 2012 ACS reports five-year aggregates for years between 2008 and 2012. These aggregates usually represent the neighborhood characteristics for 2010 as the mid-year.

2.2 Building Real Estate Portfolios

We wish to identify different types of investors in our sample by their portfolio size. We aggregate the ownership panel over investor names to build portfolios for each investor each year. While other work has used shared mailing addresses to construct portfolios, we note that our sample period saw large increases in the propensity to use professional registered agents.[6] As such, we utilize a combination of industry reports, public data filings, and name harmonization algorithms to build our portfolios and discuss the process in detail below.

Investor Identification: To start with, we create a comprehensive list of non-individual entities identified by key ownership strings such as "LLC", "Corp", "Inc", "Capital", etc. We also use CoreLogic's proprietary corporate indicator to help identify as many corporate landlords as possible. In order to focus on a final list of corporate landlords of our interest, we manually remove government, public, and non-profit entities as well as individual and family trusts. Because completely and correctly removing all family trusts is difficult, some individual or family trusts remain on our final investor list. However, we can differentiate them from those investors of our interest (e.g., long-term rentals, private equity real estate, etc.) when it comes to analysis, by manually searching and classifying the top 10,000 investors by size in our sample.[7] We show examples of parent-subsidiary pairs in Appendix A.2.

Name Harmonization: Based on our investor list, we wish to uniquely identify each investor over time even though an investor may use different names in the data. We use the RapidFuzz Python package, which calculates the Levenshtein string distance and fuzzily matches strings, to harmonize similar investor names and collapse them to represent one unique investor. This package helps mitigate concerns of names not matching due to common abbreviations (i.e. "Assoc." for "Association"), or typos (i.e. "Homes" and "Hoems").

Public Subsidiaries: We hand-collect all subsidiary names reported in each year for each publicly traded investor we identify from industry reports from SEC 10K filings. This step is crucial to identifying all entities of an investor because many subsidiary names do not

[6] Instead of tracking down professional registered agents, we leverage the fact that many of the largest firms (Corporation Services Company, Corporation Trust Company, etc.) have their offices in Delaware. Figure D7 plots the share of DE mailing addresses for non-DE homes; this share nearly quintupled around the time Invitation Homes launched the first public debt offering secured by single-family rental income.

[7] While our sample potentially underestimates the number of all investors, some methods may identify corporate entities more comprehensively, as proposed by (An et al., 2024).

resemble the name of its parent company. We collapse all property holdings of these subsidiaries into their parent company. Details and examples can be found in Appendix A.5.

Private Subsidiaries: For the firms in our data that are not publicly traded, we search through OpenCorporates, Florida Division of Corporations, and other online platforms for their subsidiaries and match them to parent companies either directly reported on the corporate listings data, or through manual search connecting the entities, as through related addresses or legal filings. Detailed descriptions and examples can be found in Appendix A.5.

Accounting for Small Investors with Similar Strings: The last step before constructing investor-level portfolios is to differentiate potentially small investors from the large investors of interest. For example, while there are a large number of houses owned by the harmonized name "Rodriguez Jose," this name corresponds to many different investors such as "Rodriguez Jose Trust" or "Rodriguez Jose LLC". To disaggregate these investors, we utilize chatGPT to identify whether investors have names that look "individual" vs. "corporate." We provide examples of individual names and corporate names to chatGPT so that it can distinguish between the two types. We then feed ChatGPT a list of 10.3 million investor names and it returns their classifications. For our specific prompt, see Appendix B. ChatGPT classifies 7.4 million names as individual-like and 2.9 million as corporate-like. For the individual-like names, we cluster them at the county level. In other words, one "Rodriguez Jose" in Los Angeles County is a different entity from another "Rodriguez Jose" in New York County. This limits the over-aggregation of individuals' portfolios while allowing for national aggregation for corporate-sounding entities. To second-check the chatGPT classifications, we manually confirm among our top 10,000 largest investors whether they appear to be aggregations of many smaller individual landlords, as in the example above, or a larger investor.

Investor-Year Holding Panels: We collapse the ownership panel within the harmonized investor names to build portfolio holdings for each investor, each year. We aggregate the number of housing units and investors' annual transaction volumes, as well as broken down by sales and purchases. This data set allows us to track the number of housing units owned, purchased, and sold by each investor each year.

As shown in Table 1, most of the largest holders of single-family real estate are the large national home-building companies such as D.R. Horton, Lennar, NVR, and the Pulte Group. These builders regularly top industry reports of the largest builders, measured by

Table 1: Categorization of the Top 20 Institutions

Rank	Name	Category	First Active	Last Observed	Avg. Holdings (units)
1	D.R. Horton	Builder	1978	2022	48,502
2	**Invitation Homes**	SFR	2012	2022	44,660
3	**American Homes 4 Rent**	SFR	2012	2022	36,525
4	Lennar	Builder	1954	2022	30,261
5	Pulte Group	Builder	1950	2022	19,267
6	**Progress Residential**	SFR	2012	2022	19,199
7	NVR	Builder	1980	2022	12,537
8	**Tricon Residential**	SFR	1988	2022	12,193
9	**Starwood Waypoint**	SFR	2015	2022	11,187
10	**FirstKey Homes**	SFR	2015	2022	10,034
11	**Home Partners of America**	SFR	2012	2022	8,426
12	Tri Pointe Homes	Builder	2009	2022	8,062
13	**Front Yard Residential**	SFR	2009	2022	6,734
14	Meritage Homes	Builder	1985	2022	6,303
15	DSLD Homes	Builder	2008	2022	5,992
16	Clayton Homes	Builder	1956	2022	5,992
17	**Amherst**	SFR	1993	2022	5,899
18	KB Home	Builder	1957	2022	5,810
19	Equity Trust Company	IRA	1974	2022	5,782
20	LGI Homes	Builder	2003	2022	5,587

Notes: Authors' calculations of mean portfolio holding size (in units) of single-family homes for the top 20 largest firms in our sample. "First Active" is the first year of business operation reported by an institution. "Last Observed" is the latest year an institution's activity is observed in our data. Portfolio holdings averaged between 2000-2022, our sample period of analysis; for companies established post-2000, the average is restricted to *active* years so as not to attenuate calculations towards zero.

revenue or production. Additionally, among the top 20 institutions, we can identify nine large LTRs: Invitation Homes, American Homes 4 Rent, Progress Residential, Tricon Residential, Starwood Waypoint, FirstKey Homes, Front Yard Residential, Amherst, and Home Partners of America. The first eight firms expressly identify as single-family rental providers, while Home Partners of America's stated business model is rent-to-own. We group Home Partners of America with the single-family rental providers as most renters do not manage to buy their homes within the 5-year required period, effectively making Home Partners of America a landlord, rather than a lender.[8],[9]

[8]For a discussion of Home Partners of America's lending and leasing activity, see "Private equity sold them a dream of home ownership. They got evicted instead." by Rebecca Burns, of *Business Insider*, July 7, 2023. Accessed at https://www.insider.com/home-partners-rent-to-own-low-success-rate-2023-5.

[9]The final firm rounding out the top 20 is the Equity Trust Company, which is an IRA (individual

These nine firms reflect the broad corporate structures adopted by the industry, beyond the media focus on private equity. Tricon Residential, Invitation Homes, and American Homes 4 Rent are all publicly traded companies as of 2023, with the latter two incorporated as Real Estate Investment Trusts (REITs).[10] The other firms—Progress Residential, FirstKey Homes, Front Yard Residential, and Amherst—are privately held. Large private equity firms and asset managers are also active in the single-family rental market: Cerberus Capital Management owns FirstKey Homes, Pretium Partners owns Progress Residential,[11] and Blackstone purchased the rent-to-own business Home Partners of America in 2021, and formerly owned Invitation Homes before it went public.

All 58 LTRs we identify in our sample collectively own 415,603 units by 2022. However, we likely undercount many portfolios as we cannot perfectly map individual deeds to parent companies due to the opaque and inconsistent naming practices discussed above. These six companies alone claim on their websites or in recent news articles to have ∼320,000 units under management, in order of descending size: Progress Residential ($85k$), Invitation Homes ($> 80k$), American Homes 4 Rent ($> 60k$), Tricon Residential ($> 36k$), FirstKey Homes ($> 34k$), and Home Partners of America ($> 28k$). The self-reported portfolios affirm that our constructed portfolios provide a reasonable approximation of the industry as a whole, even if we can, at best, provide a lower bound.

While we do not directly use portfolio size for our market-level analysis, instead aggregating holdings across firm *types* described in the next subsection, these portfolios are key inputs into our investor categorizations by affording us a measure of portfolio size.

2.3 Categorizing Firms

Using the aggregated portfolio of holdings, we categorize firms by type, purpose, and size.

Long Term Rental Companies (LTRs): Firms whose primary business upon buying properties is to hold them for longer spells and rent the units out. In short, these firms act as landlords supplying long-term rentals. This group includes many private equity real estate firms, as well as buy-to-rent firms such as American Homes for Rent, and rent-to-own

retirement account) custodian specializing in alternative assets, allowing people to invest in real estate through their retirement accounts.

[10] In January 2024, Blackstone announced plans to acquire Tricon Residential.

[11] Pretium Partners also acquired Front Yard Residential in 2021.

firms such as Home Partners of America. We require the LTRs to have an average holding period for their properties of at least 3 years, as in Bayer et al. (2020) and DeFusco et al. (2022). Figure D3 Panel (A) shows the mean holding period distributions for LTRs. Most of these firms have average holding periods of between 3 and 8 years and must lease out the units in the meantime to earn rental income between acquisition and eventual disposition. We should note, that all holding periods will be attenuated towards lower values as these firms have, for the most part, existed for less than a decade, with some growing out of the Covid-19 pandemic. Additionally, since our data ends in 2022, for any property transaction after 2019, we cannot yet differentiate whether the unit is being flipped (held for less than 3 years) or held to be rented out. As such, we remove all purchases post-2019 from the sample when calculating an investor's average holding period.

Small Landlords (SLLs): These are investors who fall outside the right tail of portfolio holdings, with fewer than 150 units. We use this group of landlords as competitors to the LTRs in local rental markets as both provide long-term rental units to tenants. We restrict to those small landlords with average holding periods of at least 3 years, as with the LTR companies, to avoid counting speculative holdings as available to rent. Finally, we allow for three types of small landlords. We define the smallest investors as having inventories of 2-5 units, likely these landlords manage their portfolios while also having another job. We define the next tier as small, professional landlords with holdings on average of 6-25 units. These investors now have enough properties under management to be considered professional landlords. Finally, we classify investors with 26-150 units as large professional landlords, these are often focused on one market.

Our main analysis compares LTR and SLL market shares, as these two groups supply rental housing in the competitive market. In addition to these two groups, we delineate three more categories to provide institutional background in the investor-owned market.

Builders: These firms primarily build new housing for sale, though in the later years of our sample, many teamed up with LTRs to provide single-family build-to-rent housing, the newest innovation in rental housing. Builders tend to hold their units for shorter periods than LTRs, as shown in Figure D3 Panel (B). Since many of these large builders build entire communities, not just individual units, most end up holding units for at least three years; some units will sell at the beginning of the community, while some will be sold at the time of community completion, which can take many years. We classify builders separately from LTRs as they do not act as landlords; instead, they expand the entire stock of single-family units, to either landlords or owner-occupants.

iBuyers: iBuyers include firms such as Zillow Offers, Offerpad, RedfinNow, and Opendoor. These firms make money by buying homes their valuation models believe are undervalued, buying at a discount, and selling quickly for a small profit. Some of these firms also perform minor renovations. They tend to make lower profit margins than other speculators and earn profits on transaction *volume*. We want to remove these large investors from our sample, as they do not act as landlords. They may, however, reallocate single-family housing units from owner-occupants to rentals depending on to whom they sell. In later analysis, we estimate that 92% of homes bought from iBuyers come from owner-occupants.

Other: We do not use this group in our main analysis. This group includes both institutional (not LTRs, builders, iBuyers, speculators, or small landlords) and individual investors who hold on average fewer than 2 units, with an average holding period larger than 3 years.

We can examine the investor type composition by breaking down the top 0.01% (1,052) largest firms ranked by average portfolio size in units. These firms comprise 50 LTRs, 247 builders, 6 iBuyers, 23 individual investors, and 726 non-categorized investors, such as banks, law firms, and other institutions. Of the 50 LTR firms, 10 are publicly traded, 18 are backed by or operate as private equity real estate firms, and 22 are other privately held companies investing in single-family rentals through various business models. Zooming out to the top 1% of firms, we are able to categorize 58 total LTR firms, 247 builders, and 8 iBuyers.

As a check that our portfolio construction matches reality, we collect reported holdings from the 57 LTRs that remain active in our sample as of the end of 2022.[12] We visit their websites and compare their reported holdings to our computed portfolio holdings. We caveat that most of the reported holdings on firms' websites report their *2023* holdings, while we only have data through *2022*, leading us to under-count total portfolio holdings in the case of recent mergers and acquisitions, such as Invitation Homes' purchase of nearly 2,300 homes in September 2023.[13] Figure 3 shows our estimated holdings in gray, overlaid with firms'

[12]The only inactive LTR in 2022 is United Development Funding, a REIT.

[13]See https://www.costar.com/article/851737351/largest-us-single-family-rental-owner-says-it-too-is-having-trouble-finding-houses-to-buy

reported holdings in the dark outlined boxes. We do fairly well in matching holdings for public companies, such as Invitation Homes and Tricon Residential, as well as the REIT American Homes 4 Rent.[14] We do less well with private entities, especially the PERE firms such as Amherst Group or Atlas Real Estate. Many of these private equity-backed funds do not even list their holdings on public-facing websites, such as Carlyle Group, Inc. or Lone Star Funds, making the comparison impossible. However, given our strong ability to match the reported holdings of the largest LTRs (AMH, FirstKey Homes, Home Partners of America, INVH, Progress Residential, and Tricon Residential), we are confident that we can capture the broader trends in LTR shares over time and across Census Tracts.[15]

3 Growth in Institutional Investors' LTR Portfolios

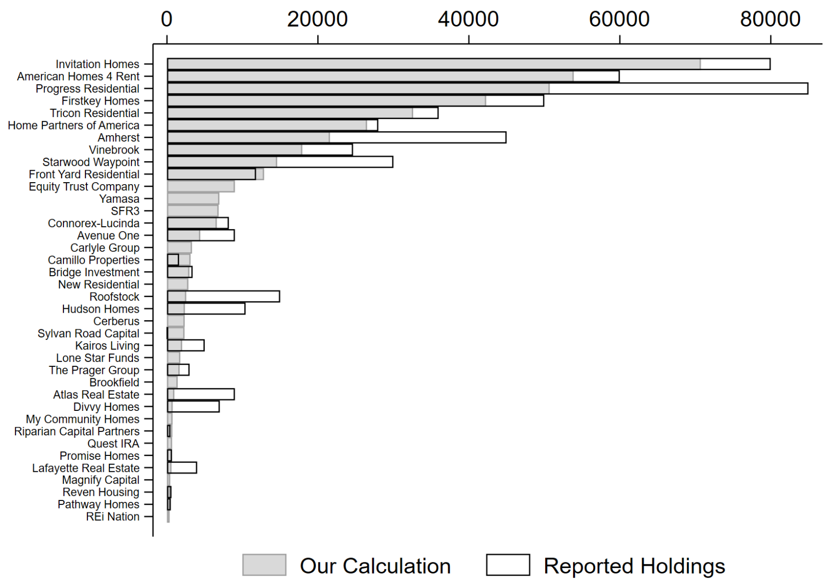
Having constructed time-varying portfolios for individual investors, we first analyze LTRs' market share relative to other large investors: builders and iBuyers. Panel (A) of Figure 4 plots the market share among the holdings of the 1,000 largest portfolios in our sample, averaged over 2010-2022, roughly corresponding to the top 0.01% of investors. Among these firms, LTRs owned about 4% of the single-family housing units in 2010, building up their market share to 71% by 2022. This corresponds to 19k holdings in 2010 to over 415k units by 2022.[16] An important sanity check, iBuyers' portfolios only showed meaningful growth post-2017, with companies like Offerpad (founded in 2015) and Zillow Offers (launched in 2018) cropping up. iBuyers never reflect a meaningful share of single-family holdings among large investors, as their business model is to buy and quickly sell homes, keeping portfolios small. Homebuilders make up the largest market share segment among our largest categorized

[14] Tricon Residential is a Canadian firm with properties across the U.S. and Canada. As such, some of our underestimation is due to not having access to Canadian deeds records.

[15] As of 2021, Pretium Partners, which already wholly owned Progress Residential, took Front Yard Residential private. As of now, the two LTRs, Front Yard and Progress Residential seem to be operating separately and have not been merged into one legal entity, so we keep them separate in the data. Similarly, as of 2021, Blackstone acquired Homes Partners of America, and as of January 2024 plans to take Tricon Residential private. We leave these firms separately identified in our table instead of aggregating to Blackstone.

[16] Authors' calculations. We admit measurement error both upwards and down: the name harmonization methods we use to aggregate subsidiaries may misattribute similar unaffiliated names to a parent company (over-aggregation), and we miss more opaquely named subsidiaries (under-aggregation). Finally, some of the LTRs (or their earlier incarnations) did exist before 2012, operating at a much smaller scale.

Figure 3: LTRs' Estimated (2022) vs. Reported Holdings (2023)

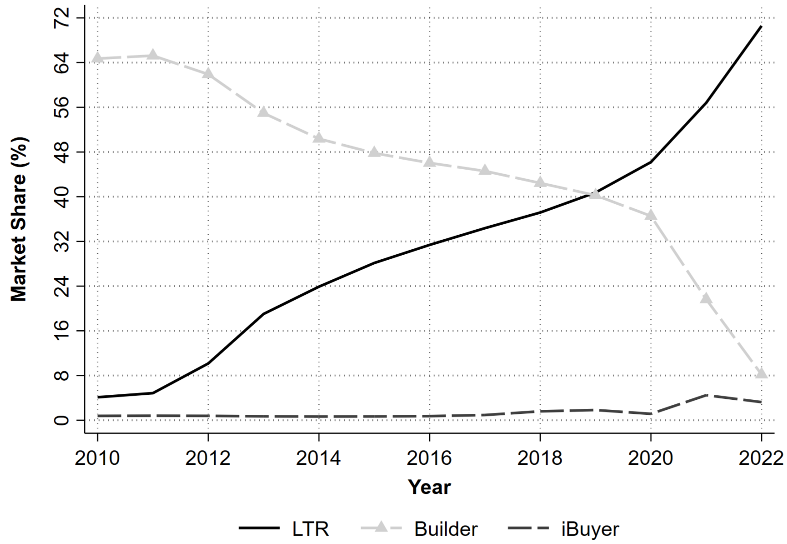


Notes: This figure compares our estimated single-family and townhome holdings as of December 2022 to reported holdings on firms' websites as of December 2023. We limit the sample of LTRs to those still active in 2022, defined as having positive single-family or townhome holdings; this removes previously active LTRs that were acquired by other entities, or which discontinued their single-family rental business. Not all firms report holdings publicly, especially true for privately held portfolios.

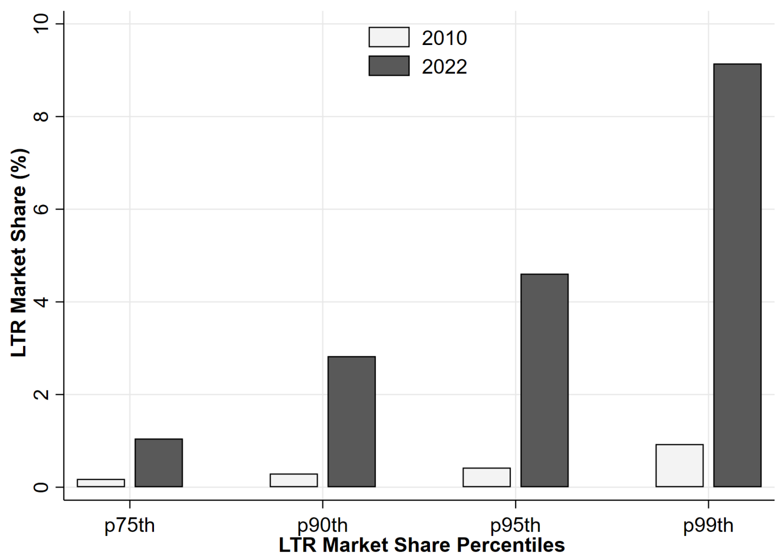
investors for most of the sample. They represented about half of investor holdings until 2016, as their market share declined. During the COVID-19 pandemic, their holdings fell quickly as new households moved into homeownership at fast rates.

These LTRs now represent a sizeable share of the total stock of single-family rental units, holding more than 415k units by 2022, and these holdings are in increasingly concentrated locations. Figure 4(B) shows how holdings have concentrated in space over time, plotting the distribution of LTR's *Tract-level* market shares in 2010 vs. 2022. In 2010, the median Tract (not shown) had an LTR market share of 0.11%, and the 95^{th} percentile Tract had 0.42%, highlighting the limited variation in investor presence across tracts at the time. By 2022, these Tracts have diverged significantly, with the median Tract having roughly 0.34% single-family units owned by LTRs. In contrast, the 95^{th} percentile LTR market share Tract saw about 4.6% of its single-family homes owned by LTRs. While most Tracts saw increasing LTR presence between 2010 and 2022, the right tail grew at a faster rate. Comparing the

Figure 4: LTR Market Shares Over Time



(A) Share Among 1,000 Largest Investors



(B) Tract Level Market Share

Notes: These figures plot the market share of single-family and townhome properties owned by investors, rather than owner-occupants. Panel (A) shows the market share among the 1,000 largest investors, as measured by the average portfolio holding size in units between 2010 and 2022. Data from CoreLogic Deeds aggregated to year level. Panel (B) plots the distribution of Census Tract level LTR market shares between 2010 and 2022, as measured by their portfolio holdings of single-family and townhomes. Data from CoreLogic Deeds aggregated to LTR-Tract-year level.

99^{th} percentile Tract in 2010 vs. 2022, LTR market share grew from 0.9% to more than 9% such that in the most concentrated Tracts, 1 in 11 homes is now owned by an LTR.

In Appendix Table C1 and Appendix Figure D4, we break down the median and national ownership as of 2022 as well as transaction shares from 2010–2022. While LTRs own only 0.3% of all housing units and only 0.4% of all single-family and townhome units, they own about 3% of all renter-occupied single-family and townhome units, highlighting their potential to impact rental supply and prices. Additionally, they've participated in nearly 7% of all single-family and townhome transactions.

3.1 Targeted Properties and Demographics

The media have described LTRs as primarily interested in acquiring single-family homes. To test this claim, we observe how census Tract-level LTR market shares evolved between 2010 and 2022 relative to SLLs' portfolios across a variety of property characteristics. Additionally, we control for local demographics as a proxy for local demand.

Motivated by media reports that LTRs prefer different products than SLLs, we collect Tract-level data from the Decennial Census and American Community Survey on a suite of property characteristics. These include the share of homes that are single-family, townhomes, in buildings with 2-4 units, in buildings with 5-49 units, or 50+ units; the share of units with 1, 2, 3, and 4+ bedrooms; the share of homes aged 1-10 years, 11-20 years, 21-40 years, or older; and the share of homes by room count. To control for local demand factors, we collect data on Tract-level demographic and socioeconomic characteristics. These include the local housing vacancy rate, the share of residents with a college education, the unemployment rate, the poverty rate, log income, and the share of the population that identifies as non-Hispanic Black, Hispanic, Asian, and White. To control for local housing market conditions, we also control for local log rents and log home values. All of the product, socioeconomic and demographic, and housing market characteristics are anchored to 2010, such that they can be interpreted as predicting inflows of landlords by type over the following decade.

Appendix Table C2 summarizes the product characteristics, demographic and socioeconomic characteristics, and landlord market share changes in our sample. Landlord market share changes are calculated between 2010 and 2022, while all other characteristics are measured in 2010. We see that in the average Census Tract, single-family houses comprise 62%

of the housing stock, with middle-density products much less common than high-density among the multi-family options. The average Tract is comprised mostly of 2 and 3-bedroom homes, and these homes tend to be older, with 42% of homes built at least 40 years ago. The average Tract has a 12% vacancy rate, is 28% college educated, and has a relatively high unemployment rate at 10% and poverty rate at 16%, since this data came from 2010 near the peak of the unemployment cycle following the recent Great Recession. The average Tract is 14% non-Hispanic Black, 5% Asian, and 16% Hispanic.

Table C2 shows how different landlords evolved between 2010 and 2022. At first glance, it seems that LTRs saw minimal market share changes, with the average Tract realizing only a 0.17 percentage point increase, measured as the share of units owned by all LTRs combined in 2022 less the share owned by all LTRs combined in 2010, multiplied by 100 to convert to percentage points. But recall that Figure 4 shows that these LTRs tend to concentrate their holdings in space. Moving along the columns, we see that the maximal Census Tract saw LTRs' market share grow by 63 percentage points. Small landlords holding 2-5 units also grew in the average Tract by 0.19%. Those with larger portfolios were stable, or declined.

We then pairwise interact these variables to create product characteristic combinations, allowing for different landlords to have preferences over 3-bedroom apartments vs. 3-bedroom single-family homes, for example. Due to the large number of product characteristics, crossing the full set of variables yields 90 two-way product combinations with positive housing shares. Because the suite of potential predictive housing characteristics is large at 90 variables, we use machine learning to better estimate how they predict changes in LTR and SLL market shares. Following Derenoncourt (2022), we use the least absolute shrinkage and selection operator (LASSO) to select which of our pairwise variable combinations is useful in predicting changes in either LTR or SLL market shares. This procedure allows us to see which combinations of property characteristics LTRs and SLLs prefer. Under our tuning and penalty parameters, LASSO selects 42/90 potential pairwise product combinations. We use these characteristics of the built environment and neighborhood demographic composition to identify product preferences by different types of landlords in the following design:

$$\Delta\text{MktShare}_i^l = \sum_j \beta_j \text{Prop}_i^j + \sum_k \gamma_k X_i^k + \delta_c + \varepsilon_i \tag{2}$$

where $\Delta\text{MktShare}_i^l$ is the observed change in market share (measured by the units in portfolio holdings), in percentage points, for a landlord of type $l \in \{LTR, SLL\}$ in Census Tract i, between 2010 and 2022. For our main specification, we define SLL to be landlords with inventories of 2-5 units since these landlords hold the overwhelming majority of units in our sample and account for over 97% of investors. Prop_i^j is our list of 42 post-LASSO selected pairwise property characteristic combinations, indexed by j and set to their 2010 values. X_i^k includes our suite of socioeconomic, demographic, and housing market controls to proxy for local demand. Finally, we include county-level fixed effects, δ_c.

We run specification 2 for both LTRs and SLLs with 2-5 units separately, implementing a linear delta method to compare point estimates across the two samples. The coefficients of our interest, β_j, reveal the landlords' preferences for different product mixes, presented in Table 2 Panel (A). Column (1) of Table 2 presents the LTRs' revealed preferences, column (2) the revealed preferences of landlords who own 2-5 units, and column (3) the difference. For ease of inspection, we limit results to those product mixes for which we estimate statistically significant differences in revealed preferences across the two landlord types. In the top row, we see that LTRs prefer mid-sized single-family homes, in line with what media reports have indicated. Increasing the share of single-family homes with 3 bedrooms by 0.1 (or 10 percentage points) in the average Census Tract would predict a differential increase in LTR market share of 0.11 percentage points, sizeable when considering the average Census Tract saw an LTR market share increase of 0.17 percentage points. These results thus confirm that these single-family rental companies are true to their name, and are providing a new set of product characteristics in the rental market relative to smaller, more traditional landlords. Moving down the rows, we see that LTRs prefer 3-bedroom homes more than bigger or smaller ones, relative to smaller landlords. They also prefer newer homes.

Panel (B) of Table 2 also plots the coefficients γ_k, which reveal how LTRs select on neighborhood composition. Relative to smaller landlords, they eschew Tracts with high vacancy and high poverty. They also tend to select Tracts with higher non-Hispanic Black and Hispanic minority shares, consistent with other reports noting their selection into minority neighborhoods (Goodman et al., 2023; Austin, 2022), and their potential to spur gentrification (Austin, 2022). We do not observe differential preferences across landlords on housing market characteristics; both landlord types prefer buying homes with lower prices, though the LTRs seem less price sensitive than the smaller landlords, likely as they have much more capital behind them. Both landlords prefer healthy rents.

Table 2: Product Characteristics' Differential Impact on Market Shares

	(1) ΔMktShare$_{LTR}$	(2) ΔMktShare$_{2to5}$	(3) Difference
Panel A: Property Characteristics			
Single Family & 3 Bed	0.620***	-0.471	1.090***
	(0.159)	(0.313)	(0.353)
Townhome & 4+ Bed	-0.501	0.789*	-1.290**
	(0.339)	(0.428)	(0.561)
2-4 Unit & 1 Bed	0.484	3.839***	-3.355**
	(0.312)	(1.244)	(1.191)
Single Family & 2-5 Room	0.408***	-0.193	0.601**
	(0.129)	(0.225)	(0.249)
2 Bed & 1-10 Year Built	-2.840***	-0.409	-2.430*
	(0.965)	(0.602)	(1.269)
3 Bed & 1-10 Year Built	0.899*	-0.487	1.386*
	(0.543)	(0.571)	(0.764)
3 Bed & 11-20 Year Built	0.880*	-0.755	1.635**
	(0.516)	(0.483)	(0.703)
3 Bed & 40+ Year Built	-1.012***	0.321	-1.332***
	(0.298)	(0.369)	(0.499)
4+ Bed & 21-40 Year Built	-0.190	0.946*	-1.136**
	(0.255)	(0.529)	(0.570)
1-10 Year Built & 6+ Room	-0.161	1.098**	-1.259**
	(0.293)	(0.502)	(0.553)
11-20 Year Built & 2-5 Room	-0.0603	2.231***	-2.291***
	(0.189)	(0.470)	(0.492)
11-20 Year Built & 6+ Room	-0.157	1.023**	-1.180**
	(0.288)	(0.479)	(0.532)
21-40 Year Built & 1 Room	-1.161	5.822*	-6.983*
	(2.303)	(3.431)	(3.929)
40+ Year Built & 2-5 Room	-0.212	0.991**	-1.204***
	(0.180)	(0.412)	(0.442)
Panel B: Demographics			
Vacancy	-0.256***	0.536***	-0.792***
	(0.0618)	(0.137)	(0.150)
College	-0.270***	-0.0272	-0.243
	(0.0993)	(0.116)	(0.158)
Unemployment	-0.230	-0.408	0.178
	(0.177)	(0.366)	(0.398)
Poverty	-0.402***	1.446***	-1.848***
	(0.128)	(0.244)	(0.266)
Non-Hispanic Black	0.570***	0.189*	0.381**
	(0.144)	(0.114)	(0.191)
Asian	0.0647	0.434***	-0.370**
	(0.0991)	(0.123)	(0.164)
Hispanic	-0.0156	-0.290**	0.275**
	(0.0925)	(0.126)	(0.137)
Log Rent	0.0195***	0.0167**	0.003
	(0.00577)	(0.00722)	(0.009)
Log Home Value	-0.0253***	-0.171*	0.146
	(0.00700)	(0.0899)	(0.089)
Log Income	0.00315	0.116	-0.113
	(0.0158)	(0.0976)	(0.097)
Observations	78,644	78,644	78,644

Notes: This table shows the results of estimating Equation 2 for LTRs (column (1)), SLLs with 2–5 units (column (2)), and the difference in their estimates calculated using a linear delta method. Columns (1) and (2) are cross-sectional regressions at the Census Tract level and include county fixed effects. Standard errors in parentheses, clustered at the county level. Significance: *** p<0.01, ** p<0.05, * p<0.1.

In sum, LTRs seem to be targeting newer, mid-size single-family housing stock in neighborhoods with healthy rental markets, in particular those with low vacancy and poverty rates, in high-minority areas. They also show differential preferences for neighborhood characteristics, opening up concern for potential selection on socio-economic or demographic characteristics, as highlighted in Lee and Wylie (2024); Giacoletti et al. (2024).

4 Research Design and Identification

In this section, we exploit these differential preferences by SLLs vs. LTRs along with the decline in property management costs to induce exogenous variation in LTR's willingness to enter a given housing market, relative to existing smaller landlords. We then estimate the impact of rising LTR shares on house prices. We begin with a discussion of the endogeneity concerns with a naive ordinary least squares regression:

$$\Delta Y_{it} = \alpha + \beta \Delta LTRshare_{it} + \varepsilon_{it}. \quad (3)$$

Here, ΔY_{it} is the annual change in the outcome of interest for Census Tract i in year t, such as house price or rents. $\Delta LTRshare_{it}$ is the annual change in the share of single-family homes in Tract i owned by large LTRs in year t.[17] The coefficient of interest is β, which captures the impact of rising ownership shares by large LTRs on the local housing market.

Equation 3 suffers from many potential biases. The first concern is simultaneity bias: unobserved location characteristics could be driving *both* housing market dynamics and LTR entry. For example, large LTRs enter places with rising rental demand for single-family homes brought by job entries that pay high wages (Qian and Tan, 2021). These job entries also raise the demand for owning homes and increase local house prices. In the presence of such a positive housing demand shock, OLS estimates of LTR's impact on house prices will have a positive bias. Second, reverse causality could lead locations with higher housing returns/growth in rents to attract LTRs, biasing the OLS estimate upward. Third, we could underestimate LTRshare$_{it}$ due to measurement error, leading to attenuation bias in $\hat{\beta}$. Given the endogeneity concerns of naive OLS estimates, we construct an instrument that generates plausibly exogenous variation in the entry of LTRs over time and space.

[17]This notation is equal to $\Delta MktShare_i^{LTR}$ from Equation 2, but since we are no longer keeping track of SLL market shares, we explicitly refer to LTRs name in the variable for ease of exposition.

Addressing the aforementioned endogeneity issues, some studies have utilized mergers as an identification strategy (Gurun et al., 2022; Austin, 2022). However, this approach has limitations due to the non-overlapping nature of many large LTRs' property holdings and the market-specific focus of mergers. Additionally, this strategy relies on two companies having accrued significant SFR portfolios; it is not well-suited to study the early phase of the industry in which institutional investors bought from small investors or owner-occupants. Another strategy involves the Fannie & Freddie First Look program, which is primarily relevant to real estate owned (REO) and foreclosure sales (Lambie-Hanson et al., 2022). Given the significant decline in such sales since 2013, this strategy offers diminished predictive power for investor entry in more recent times; indeed, the industry began to take off after 2013Q4 when Blackstone introduced the first public debt offering securitized by the rental income generated by its portfolio of single-family homes.[18]

In contrast, we propose a novel shift-share instrument that capitalizes on the differing preferences of small landlords (SLLs) and LTRs for certain types of properties, along with the temporal decrease in costs related to managing rental properties in a decentralized manner. We posit that LTRs transition into single-family landlords predominantly when the management of decentralized properties becomes more feasible and only in areas with an ample existing stock of single-family homes that meet their preferences.

4.1 Cross-Sectional "Share" Variation: LTR Product Suitability

First, we construct the "share" component of our instrument that captures the differences across neighborhoods in the product characteristics preferred by LTRs relative to those by SLLs. We keep the estimated coefficients $\hat{\beta}_j$ that are statistically significant in Column (3), Panel A of Table 2. These coefficients capture product characteristics differentially favored by LTRs, relative to traditional SLLs. We multiply these coefficients with the set of Census Tract product characteristics in 1990, denoted by $\text{Prop}_i^{1990,j}$'s:

$$S_i = \sum_j \hat{\beta}_j \times \text{Prop}_i^{1990,j}. \tag{4}$$

This yields a "suitability" index S_i that measures whether a Tract had existing properties more in line with what LTRs would prefer to buy, relative to traditional small landlords,

[18] "Blackstone Issuing Bonds Backed By Single-Family Rental Payments," *Bloomberg News*. 10/23/2013.

during the 2010-2022 period. Instead of using contemporaneous product characteristics, which would also capture new supply or renovations responding to landlords' demands, we use 1990-lagged characteristics. This ensures that concurrent market characteristic trends are not driving house price changes in response to our instrument. On the other hand, housing stock characteristics tend to be slow-moving as homes are expensive to renovate and slow to build, hence correlated with today's product characteristics favored by LTRs. Note the "suitability" index captures product preferences of LTRs that are orthogonal to any influence of socioeconomic and demographic variables since we do not include their coefficients from Panel B of Table 2, mitigating the selection concerns raised by Giacoletti et al. (2024); Lee and Wylie (2024). The cross-sectional differences in neighborhoods' suitability indices serve as local "pulling factors" to attract LTRs to enter as landlords.

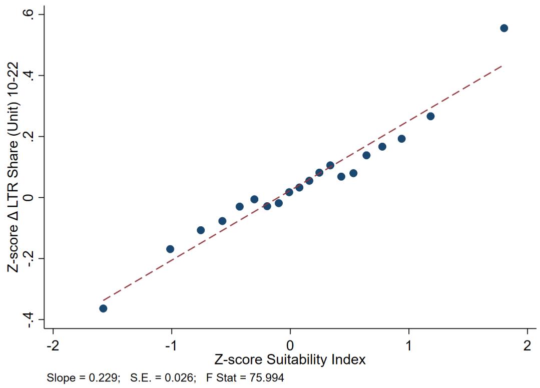
The binned scatterplot in Figure 5 displays the relationship between the Z-score of our suitability index, S_i, and the Z-score of the change in LTR share in a given Tract from 2010 to 2022, $\Delta LTRShare_i$. Note that since most Tracts in our sample had no LTR entry as of 2010, the y-axis captures the entire industry growth over those 13 years. The figure shows that, at the cross-sectional level, our instrument is likely to satisfy the relevance condition: there is a strong, positive relationship between a Tract's built environment in the 1990s being suitable for LTRs, and LTR's later entry. Interpreting the slope in Panel (A) for our regression sample for house prices, we see that a 1-standard deviation (0.43) increase in the Suitability Index predicts a 0.23-standard deviation ($1.07 \times 0.23 = 0.25$ percentage points) greater actual increase in LTR market share during our sample period. The F-statistic is around 76. The slopes for our regression samples for rents in Panel (B) and homeownership in Panel (C) as local housing market outcomes are all similar, with high F-statistics.

4.2 Temporal "Shift" Variation: Declining Management Costs

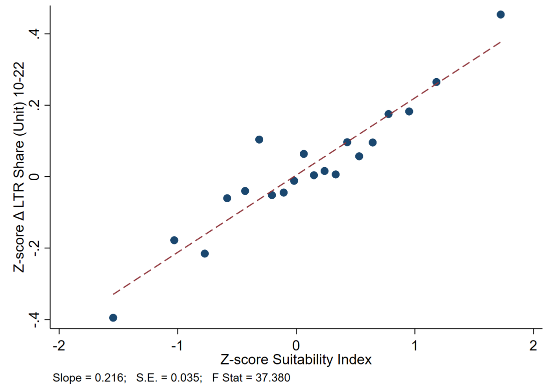
Next, we build the "shift" component of our instrument. In talking with industry professionals, many brought up the rise of Online Property Management (OPM) software as a key technology enabling the management of multiple sites. Even today, 65% of rental units are in multifamily buildings according to the 2022 Census, a share that has persisted since 2010.[19] This high multifamily share reflects the historical challenge of providing services

[19] Authors' calculations using 2022 national ACS data, excluding rentals in mobile homes, boats, or RV's.

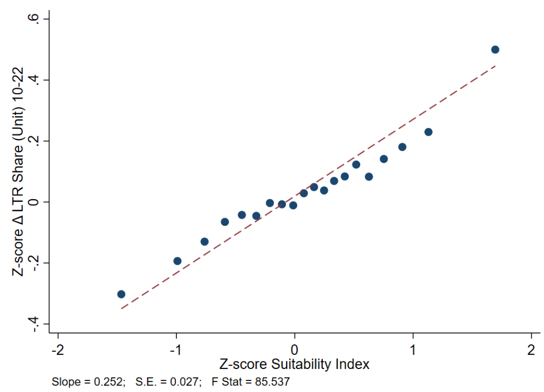
Figure 5: Partial First Stage, Conditional on Outcome Sample



(A) Prices



(B) Rents



(C) Homeownership

Notes: This figure shows a binned scatterplot as well as a linear fit of the Z-sore of $\Delta LTRshare_i$ between 2010–2022 against the Z-score of the Suitability Index, S_i constructed in Equation 4. We include county-level fixed effects to control for unobserved local heterogeneity and local house price elasticities of supply borrowed from Baum-Snow and Han (2024).

to geographically dispersed properties relative to having a management office or superintendent in a multifamily building.[20] The OPM platforms has enabled the management of decentralized properties without an on-site superintendent or staff.

We collect data on funding rounds and amounts flowing into the OPM industry from industry lists, Preqin, and Crunchbase, which also provide firms' industry categories. Our

[20]See for example, the discussion of the difficulty of site decentralized in this primer on the single-family rental debt market put together by Amherst Pierpont Securities, LLC: https://apsec.com/site-content/uploads/2021/04/APS-SFR-Primer-April-2021-FINAL.pdf

final sample has data on 23 OPMs, for which we have at least one funding round with an amount reported. We include funding rounds denoted as angel, venture, pre-seed, seed, series A/B/C/D, debt financing, as well as post-IPO equity gains in the cumulative funding amount. For funding rounds, we also include a "round" when a firm is acquired or taken private. Importantly, we differentiate between software meant only to allow rental payments (of which there are many more firms), instead restricting to firms that provide additional services such as rental listing, lease contracting, maintenance requests, etc.

Figure 6 plots the cumulative amount and rounds of funding OPM companies received from venture capitalists (VC). The industry has seen marked growth, with the total funding raised in 2003 wholly attributable to RealPage's Series A round in December 2003 totaling \$31.6 million. By the end of 2022, over \$2 billion has flowed into the OPM industry spread over more than 80 funding rounds. Consistent with the uncertainty around the single-family rental industry's success, 2014 seems to mark a turning point with OPM funding amounts accelerating over the next two years.[21] Funding amounts slowed even as rounds progressed steadily, until booming again during the COVID-19 era.

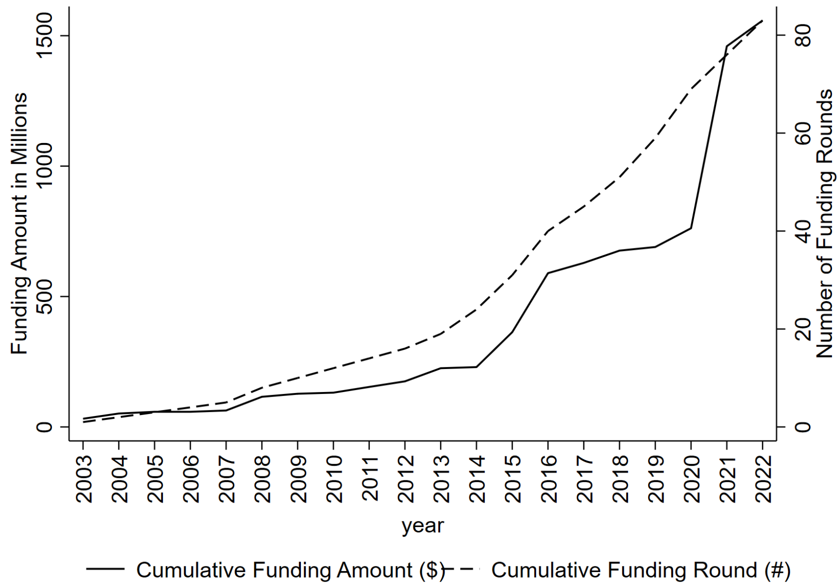
This variation in funds flowing into OPM software acts as a national "push" for landlords to enter the rental market, as increased competition offers cheaper property management solutions.[22] This is true particularly for LTRs and larger landlords as many of these OPMs have a minimum unit requirement.[23] As an example of declining *average costs* as landlords' portfolios grow, we present Buildium's pricing advertisement from October 2024 in Figure 7. The plans offer many of the same features such as offering a suite of "accounting, maintenance, tasks, violations, resident & board member communications, and online portals," with additional features by the plan. For example, the Growth plan offers property inspections, which are only available in the Essential plan for an additional fee. If we assume

[21] Between 2012 and 2014, industry reports were unsure if Blackstone's single-family rental portfolio would be just a good trade (capital gains associated with buying homes at the bottom of the market and selling during recovery) or signaled the beginning of a new industry. After Blackstone's first debt offering was securitized by single-family rental income in 2013Q4, cumulative issuance grew steadily through 2021Q1 according to the aforementioned Amherst Pierpoint report.

[22] For examples of how LTRs use these platforms, see the documentation for Invitation Homes and American Homes for Rent in Appendix Figure D5.

[23] For example, AppFolio, one of the largest OPM platforms, requires a 50 unit minimum to use their software, or a minimum monthly spend of \$280, which translates to 200 units at minimum unit cost. Their "plus" and "max" memberships require higher payments and unit counts. This can be visualized in Appendix Figure D6. https://www.appfolio.com/property-manager accessed on 10/9/2024.

Figure 6: Time Series of VC Funding



Notes: This figure shows the cumulative funding amount or rounds raised by Online Property Management Platforms, as collected through industry reports, Crunchbase, and Preqin. The y-axis reflects the total funding or rounds raised, relative to the total amount as of 2022.

that landlords utilize only the main features included in every plan, in addition to accepting online payments from their tenants, we can compare average costs across plans.

Figure 7 plots the average cost per unit for Buildium's Essential and Growth plans. We assume the "starting at" prices represent the minimum fixed cost of a plan, and set each unit's marginal cost to equal the price of an incoming Electronic Funds Transfer (EFT). In both plans, the monthly cost of these plans falls steeply as portfolios increase; however, these costs are quite high for small landlords, and most landlords are indeed small. Appendix Figure D2 shows that more than 97% of investors own fewer than 5 units. A landlord with 5 units would pay $37.20/unit, or $186/month total, under the Growth plan, or $13.59/unit, or $67.95/month total, under the Essential plan. At 320 units, the Premium plan has the cheapest average cost, at $1.17/unit, or 3.1-8.6% the average cost of the 5-unit landlord.[24]

[24]Why don't small landlords just hire a property manager who can manage a larger scale portfolio and pass on the OPM cost savings to the small owner? In discussions with property managers, we learned they generally charge either a flat rate of around 10% of the unit's rent or a fee per unit of $100-$200. Both of these fee structures swamp the benefit of the potential OPM cost savings, suggesting that small landlords

This example demonstrates the cost advantage that large firms have in adopting OPM platforms. In addition to the cost advantage, these platforms enable remote management and monitoring of a landlord's portfolio. Rental housing is an industry characterized by significant "home bias," in part driven by the difficulty of managing properties when living far away (Levy, 2022). By removing the spatial barriers to management and operations, i.e. through remote locks to allow for tours or centralizing maintenance staff rather than having a supervisor in each building, these platforms enable more geographically dispersed ownership. We will caveat that LTRs do tend to concentrate their holdings within cities, suggesting there remain important local economies of scale, even as OPM enables operations to disaggregate from multifamily to single-family residences.

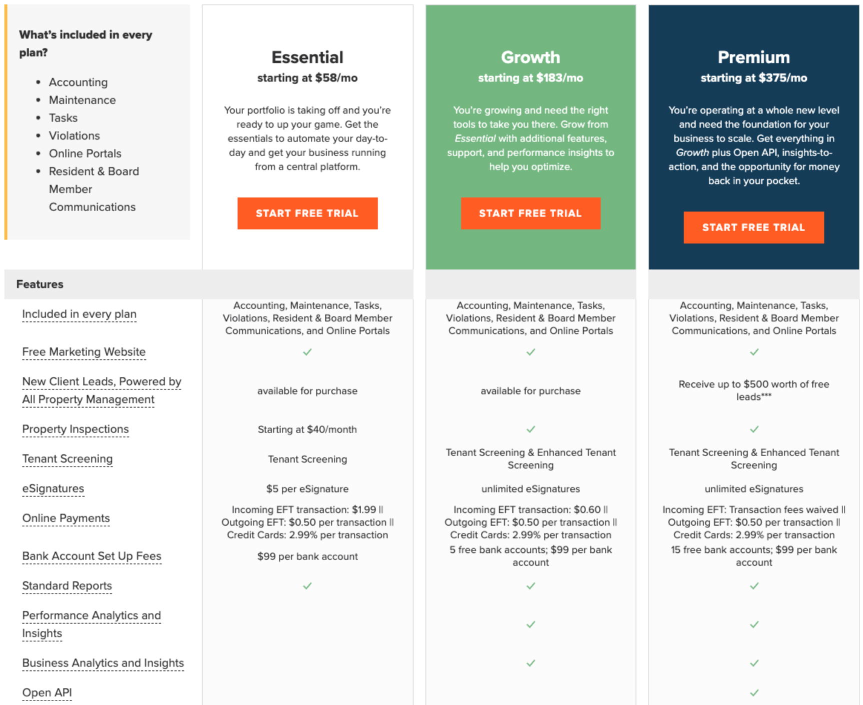
4.3 Building the Full Instrument

Finally, we devise an instrumental variable by integrating both the "shift" and "share" elements. The basic intuition is that the interaction of the temporal variation in the cost of managing single-family properties, shifts in the potential market size for OPM, and local product suitability together act as "pushing" and "pulling" factors encouraging firms to venture into the LTR business in a local housing market.

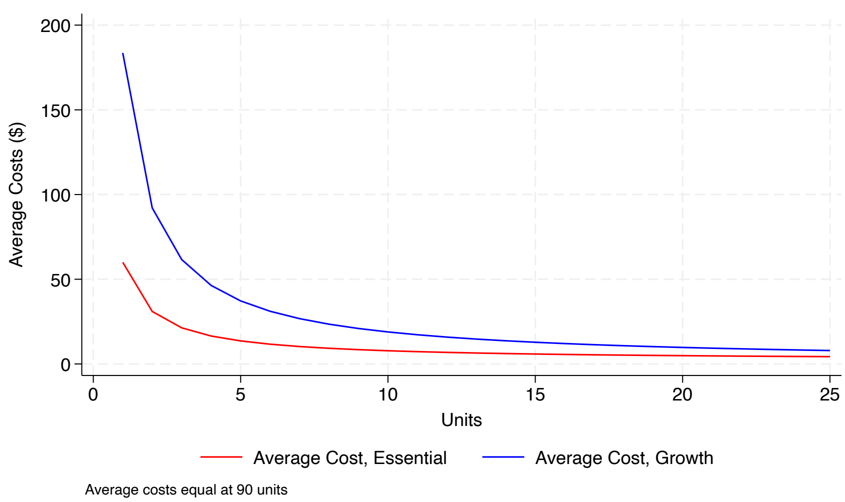
To implement this, we first standardize the cumulative VC funding from 2003 to 2022 into an empirical distribution function, ranging from 0 to 1, represented as $\hat{F}_{\text{funding}}(t)$. We further collect the yearly aggregate of property management (PM) establishments nationwide from the County Business Patterns (CBP) as a measure of potential market size for OPM. For each Census Tract i within county c, we create a "leave-one-out" metric, $|PM|_{(-c)it}$, that aggregates the yearly PM establishments nationwide but omits the PM establishments from the Tract's own county. This measure reflects the temporal variation in the nationwide potential customers for adopting OPM platforms, explicitly excluding the influence of local PM industry growth. The "leave-one-out" method removes any correlated idiosyncratic shocks within a county that may arise from the industry-location dynamics of PM expansion. To create our full instrument, we take the product of Tract level suitability index S_i, the normalized cumulative VC funding annually $\hat{F}_{\text{funding}}(t)$, and the "leave-one-out" market size metric $|PM|_{-c,it}$. Finally, we standardize the instrument into a Z-score for ease of inspection

may not benefit from these technologies.

Figure 7: Average OPM Costs by Portfolio Size



(A) Buildium's Pricing Menu



(B) Average Costs, by Plan

Notes: Panel (A) shows a screenshot of Buildium's pricing advertisement from https://www.buildium.com/pricing/?plan=growth&planTerm=monthly&unitsCount=1 accessed October 9, 2024. Panel (B) plots the average cost per unit using the two lower-cost Buildium plans, Essential and Growth, authors' calculations.

and interpretation. Formally, our instrument, IV_{it}, is defined as:

$$IV_{it} = \text{Z-Score}\left(S_i \times \hat{F}_{\text{funding}}(t) \times |PM|_{(-c)it}\right). \tag{5}$$

4.4 Two-Stage Least Squares Specification

We estimate the relationship between the rising LTR shares and local housing market outcomes using the following changes-on-changes specifications, consistent with the canonical applications of shift-share instruments in Bartik (1991) and Blanchard and Katz (1992):

$$\begin{aligned}
&\mathit{OLS}: & \Delta Y_{it} &= \beta \Delta LTRshare_{it} + \boldsymbol{W}_{it}'\Gamma + \delta_{ct} + \varepsilon_{it}, && (6)\\
&\mathit{First\ Stage}: & \Delta LTRshare_{it} &= \alpha \Delta IV_{it} + \boldsymbol{W}_{it}'\mu + \delta_{ct} + \epsilon_{it}, && (7)\\
&\mathit{Second\ Stage}: & \Delta Y_{it} &= \tilde{\beta} \Delta \widehat{LTRshare}_{it} + \boldsymbol{W}_{it}'\tilde{\Gamma} + \delta_{ct} + \tilde{\varepsilon}_{it}. && (8)
\end{aligned}$$

In equation 6, the coefficient β denotes the OLS estimate of the effect of $\Delta LTRshare_{it}$, the Z-score of the annual change in the share of single-family homes owned by large LTRs in a given year t relative to year $t-1$, on ΔY_{it}, the annual change in the housing market outcome, Y_{it}, in Census Tract i in year t. On the OLS equation's right-hand side, we control for baseline 2010-level socioeconomic and demographic Tract characteristics, encapsulated by the vector $\boldsymbol{W}_{it}$ and the interaction of county and year fixed effects, denoted by δ_{ct}. The baseline controls, $\boldsymbol{W}_{it}$, also incorporate the housing supply elasticity at the Tract level, as estimated by Baum-Snow and Han (2024) between 2000 and 2010. This measure intends to reflect local land-use policies and geographical factors that might influence both the suitability for LTRs and housing prices. Moreover, in specifications for robustness checks, we additionally account for Tract-specific changes in housing prices, expressed in percent difference during the housing market's expansion phase (2000–2006) and contraction phase (2006–2010), to control for the price dynamics preceding our study period (2010–2022). As we cannot control for both the Tract level housing dynamics and local supply elasticities *and* a Tract fixed effect, we instead include county-by-year fixed effects, δ_{ct}, to capture unobservable temporal variations in housing market conditions within counties due to regional cycles.

Equation 7 details the first-stage regression that estimates the relationship between the annual change in our instrument, ΔIV_{it}, and the Z-score of the actual change in LTR share,

$\Delta LTRshare_{it}$. Equation 8 presents the second-stage regression, where the coefficient $\tilde{\beta}$ quantifies the impact of the *instrumented* change in LTR share, $\Delta \widehat{LTRshare}_{it}$ on the local housing market outcome. In Equations 7 and 8, $\boldsymbol{W}_{it}$ include the housing supply elasticities in our baseline specification, as well as boom and bust dynamics in our robustness checks, but *not* the baseline Tract characteristics as our instrument is built already orthogonalized with respect to these characteristics. We also include county-by-year fixed effects, δ_{ct}. We cluster standard errors at the county level and weight each observation by the number of homes within the Tract in 2010 across all specifications.

Identifying Assumption and Validity Checks

To identify the causal impact of rising LTR shares on the local housing market, the exclusion restriction for the 2SLS estimator is that the shift-share instrument for changes in LTR market share must be orthogonal to omitted characteristics that are correlated with the *changes* in housing market outcomes, conditional on the specified baseline Census Tract characteristics and fixed effects. This identifying assumption can be formally stated as:

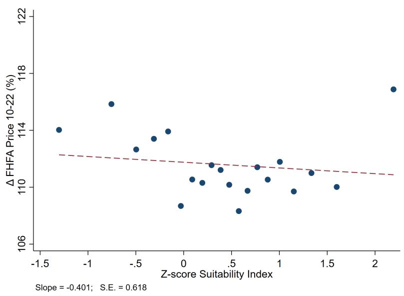
$$\mathbb{E}[IV_{it} \times \tilde{\varepsilon}_{it} | \boldsymbol{W}_{it}, \delta_{ct}] = 0. \tag{9}$$

Goldsmith-Pinkham et al. (2020) further show that identification by these shift-share instruments hinges on exogenous growth in *changes* applied to baseline shares. This allows the baseline shares (here, our Suitability Index) to be correlated with prices and rents in *levels* while assuming the baseline shares are exogenous to *changes* in the outcome variable. Although this assumption cannot be directly tested, we provide corroborating evidence that our instrument is indeed uncorrelated with unobserved determinants of local housing market changes. Specifically, we perform a set of spatial placebo tests for outcomes between 2010 and 2022. The intuition is that our identification assumption requires the rise of LTRs to be the only channel through which our Suitability Index can influence changes in local housing outcomes. So in locations *without* the LTR entry, Tracts that are more suitable for LTR entry as predicted by our instrument should not observe similar changes in local housing market outcomes as those suitable Tracts in locations that *had actual* LTR entry.

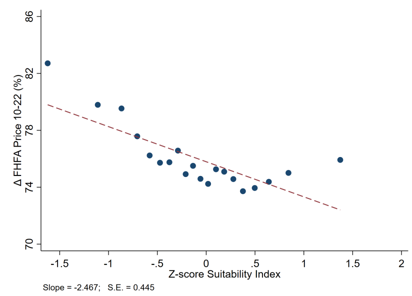
Figure 8, Panel A provides a visual check that locations in which LTRs had positive market share as of 2022 realize no significant price impacts. On the other hand, locations left untreated by LTRs see a significant negative slope in house prices. If LTRs selected neighbor-

Figure 8: Changes in Entry vs. No-Entry Tracts

A. Prices

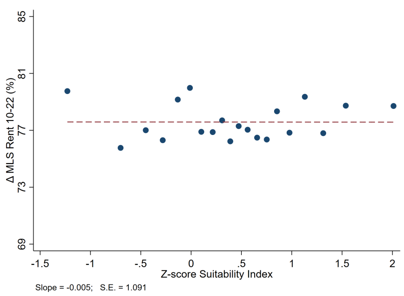


(A) LTR entry

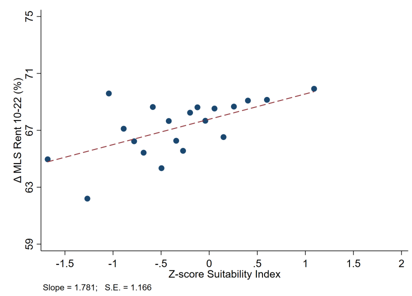


(B) No LTR entry

B. Rents

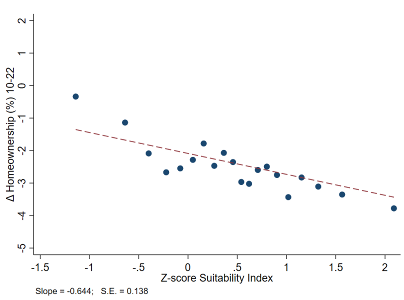


(C) LTR entry

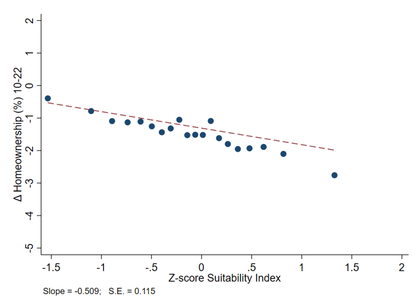


(D) No LTR entry

C. Homeownership



(E) LTR entry



(F) No LTR entry

Notes: This figure shows the binned scatterplot of total house price and rent changes between 2010 and 2022 against our Suitability Index, S_i, controlling for county fixed effects and local house price elasticities of supply from Baum-Snow and Han (2024). We split the sample into those Tracts with positive LTR entry by 2022, versus those without any entry over the same period.

hoods with unobserved demand shocks correlated with the baseline shares, our Suitability Index, we would expect similar slopes across the two samples. Instead, we see clear divergence among neighborhoods of similar suitability corresponding to their treatment status. Relative to the no-entry locations, LTRs seem to prop up prices, conditional on similar suitability consistent with Lambie-Hanson et al. (2022), and the observation in Hanson (2024) that LTRs entered declining markets and subsequently increased prices. Similarly, Panel B demonstrates that locations treated by LTRs realize a much smaller impact on rents than locations untreated by LTRs. These raw data support the argument that LTRs put downward pressure on rents, conditional on local suitability, either through achieving economies of scale (Coven, 2024) or expanding the renter supply (Barbieri and Dobbels, 2024; Chang, 2024). Finally, Panel C shows locations treated by LTRs experience a larger decrease in homeownership rate than locations untreated by LTRs, with a 26.5% larger estimated slope.

5 Results: Prices, Rents, and Homeownership

We estimate equations 6, 7, and 8 in a changes-on-changes specifications. All specifications use annual price changes deriving from the Federal Housing Finance Agency's House Price Index, and changes in market shares are based on LTR's holding share of single-family and townhouse *units* in a Tract.[25] While we presented the time series of VC funding amounts and rounds, we use time-series variation in funding *amount*, due to its more convex distribution, which ensures it will be less collinear with time fixed effects. We cluster standard errors at the county level to allow for correlations across Tracts and over time.

First Stage Results

We implement Equation 7 and present the first stage results in Table 3. Panel A presents the first stage using our regression sample for house price as the outcome. Working across the columns we move from less- to more-restricted samples in terms of LTRs' entry and growth. In Column (1), we find a 1 standard deviation increase in ΔIV increases the annual change of LTRs' market share by 0.112 standard deviations, statistically significant at the 1% level.

[25] In unreported results, we also run the specifications using LTRs' share of single-family and townhouse *value*. The findings are broadly consistent.

Given a sample standard deviation of 0.131 p.p. for $\Delta LTRshare$, this implies an increase of $0.112 \times 0.131/0.02 = 73.4\%$ relative to a Tract that experiences a mean $\Delta LTRshare = 0.02$ p.p. The first stage F-statistic is above 44, suggesting a strong first stage.

As we move across the columns and restrict our sample of Tracts, we find that the instrument has a smaller impact on annual $\Delta LTRshare$, and the Tracts have higher baseline $\Delta LTRshare$. Moving from Column (1) to Column (2), the mean $\Delta LTRshare$ increases from 0.02 p.p. to 0.059 p.p., while the point estimate rises from 0.112 to 0.21. Applying the same algebra as above, in Tracts with positive LTR entry as of 2022, a 1 standard deviation increase in annual ΔIV predicts a 46.6% increase in LTRs' market share, which is a smaller impact than in Column (1).[26] In Column (3), we restrict the sample to Tracts in the top 10 percentiles of LTR entry as of 2022. A 1 standard deviation increase in annual ΔIV predicts a $0.233 \times 0.131/0.167 = 18.3\%$ increase in LTR market share, an even smaller impact than in Column (2). This attenuation comes from the fact once LTRs have bought a significant portion of the local market, there are fewer marginal homes available for them to buy, so we would expect larger responses in new neighborhoods vs. those with already high LTR entry.

We next re-estimate Equation 7 using our regression sample for rents as the outcome. While the first stage method has not changed, the sample of Tracts has. So we present the relevant first stage in Table 3, Panel B. Our observation count is much lower in the sample of Tracts with hedonic MLS rent index available relative to the sample with house price index available, highlighting the differences in geographic coverage.

As in Panel A, the columns in Panel B of Table 3 again reflect increasingly restrictive samples based on end-of-sample LTR entry. In Column (1), we see that a 1-standard deviation increase in our instrument leads to a statistically significant increase in annual LTR entry of 0.121 standard deviations. In this sample, a Tract with a 1-standard deviation increase in ΔIV experiences a $0.121 \times 0.295/0.078 = 45.8\%$ increase in LTRs' market share, given the sample mean and standard deviation of $\Delta LTRshare$. Moving to Column (2) of Panel B in Table 3 and applying the same algebra above, we see that a 1-standard deviation increase in ΔIV translates to a $0.144 \times 0.295/0.131 = 32.4\%$ increase in LTRs' market

[26] We use the full sample in Column (1) to define the Z-scores of the changes in LTR market share. With a sample standard deviation of 0.131 p.p. for $\Delta LTRshare$, a 1 standard deviation increase in annual ΔIV predicts an additional $0.21 \times 0.131 = 0.0275$ p.p. increase in LTRs' market share in Column (2). Relative to a Tract that experiences a mean $\Delta LTRshare = 0.059$ p.p., this represents a 46.6% increase in LTRs' market share.

share in locations with positive LTR entry as of 2022. In Column (3), further restricting the sample to Tracts in the top 10 percentile of LTR entry, a 1-standard deviation increase in ΔIV translates to a $0.070 \times 0.295/0.226 = 9.1\%$ increase in LTRs' market share, and is statistically significant at the 10% level only.

Panel C presents the first-stage results using our homeownership sample. This is the most comprehensive dataset, as it comes from the ACS and covers *all* tracts. The columns progress from less- to more-restricted samples based on LTRs' entry and growth. In Column (1), a 1 standard deviation increase in ΔIV increases the annual change in LTRs' market share by 0.095 standard deviations, statistically significant at the 1% level. Given a sample standard deviation of 0.178 p.p. for $\Delta LTRshare$, this implies an increase of $0.095 \times 0.178/0.026 = 65\%$ relative to a Tract with a mean $\Delta LTRshare = 0.026$ p.p. The first-stage F-statistic exceeds 53, again indicating a strong first stage. Restricting the sample further across the columns shows a reduced economic impact of the instrument on $\Delta LTRshare$ but a higher baseline $\Delta LTRshare$ in Tracts. In Column (2), the mean $\Delta LTRshare$ rises from 0.026 p.p. to 0.08 p.p., while the point estimate increases from 0.095 to 0.161, significant at the 1% level. In these Tracts, a 1 standard deviation increase in ΔIV predicts a $0.161 \times 0.178 = 0.0286$ p.p. increase in LTR market share. Relative to the mean $\Delta LTRshare = 0.08$ p.p., this represents a 35.8% increase, smaller than in Column (1). In Column (3), a 1 standard deviation increase in ΔIV predicts an increase of $0.154 \times 0.178/0.189 = 14.5\%$ in LTR market share, showing an even smaller effect than in Column (2).

Endogenous OLS vs. Two-Stage Least Squares

Panel A of Table 4 presents the second-stage results, where the dependent variable is the percent change in house prices. Working across the columns, we move from less to more restricted samples, as in Table 3. In Column (4), a 1 standard deviation increase in the instrumented annual change in LTRs' market share, $\Delta \widehat{LTRshare}_{it}$, induces an additional annual change in the FHFA house price index of 1.575 p.p., statistically significant at the 1% level. As for other drivers of house price growth, we observe less price growth in more elastically supplied Census Tracts, as expected. The point estimate implies an annual elasticity of house price change with respect to LTR share of 12.02, meaning a 1 p.p. annual increase in LTRs' market share would induce a 12.02 p.p. (= 1.575 / 0.131) higher rise in

Table 3: First Stage Results

	(1) Full Sample	(2) Δ LTR $\geq 0\%$	(3) Δ LTR in Top 10pct
		A. Prices	
Z-score Δ IV	0.112***	0.210***	0.233***
	(0.017)	(0.031)	(0.047)
Housing Supply Elasticity	-0.059**	-0.092	-0.165
	(0.026)	(0.061)	(0.138)
Observations	445,176	150,711	41,468
F-Stat	44.33	45.44	24.18
Δ LTR Mean (%)	0.0200	0.059	0.167
Δ LTR S.D. (%)	0.131	0.203	0.341
		B. Rents	
Z-score Δ IV	0.121***	0.144***	0.070*
	(0.025)	(0.037)	(0.037)
Housing Supply Elasticity	0.014	0.037	0.071
	(0.073)	(0.116)	(0.174)
Observations	92,614	56,322	30,030
F-Stat	23.15	15.14	3.603
Δ LTR Mean (%)	0.0780	0.131	0.226
Δ LTR S.D. (%)	0.295	0.337	0.422
		C. Homeownership	
Z-score Δ IV	0.095***	0.161***	0.154***
	(0.013)	(0.020)	(0.022)
Housing Supply Elasticity	-0.022	-0.032	-0.008
	(0.030)	(0.078)	(0.163)
Observations	818,313	272,563	96,638
F-Stat	53.87	67.86	47.68
Δ LTR Mean (%)	0.0260	0.0800	0.189
Δ LTR S.D. (%)	0.178	0.258	0.387

Notes: This table shows the first stage results for prices, rents, and homeownership. We control for Tract level house price elasticity of supply from Baum-Snow and Han (2024). All specifications include county-by-year fixed effects. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

house prices. This result suggests that measurement error and simultaneity contributed to an overall downward bias in the endogenous OLS estimate in Column (1). Notably, a 1 p.p. increase in LTRs' market share over one year is large; a Tract experiencing a 1 standard deviation above the mean change in LTR share would only realize a 0.151 p.p. (= 0.02 + 0.131) annual change in LTR share, implying a 1.82 p.p. higher increase in house prices. Over this period, house prices grew on average by 4.49 p.p. per year, such that an increase in LTR share of 1 standard deviation above the mean would see a total annual increase of 6.31 p.p., with LTR entry explaining about 29% of the annual price increase.[27]

Moving on to Column (5), which leverages *intensive* margin variation in LTR share, excluding the sample of Tracts without LTR entry in 2022, the point estimate falls to 0.763, statistically significant at the 1% level. This estimate implies an annual elasticity of house price change with respect to LTR share of 5.82 (= 0.763 / 0.131). A Tract in the positive LTR entry subsample experiencing a 1 standard deviation above the mean change in LTR share would only realize a 0.262 p.p. (= 0.059 + 0.203) annual change in LTR share, implying a 1.52 p.p. higher increase in house prices.[28] In Column (6), among Tracts in the top 10th percentile of LTR entry as of 2022, the point estimate falls to 0.687 and is statistically significant only at the 10% level. The implied price elasticity is 5.24, lower than that in Column (5), perhaps reflecting the homeowner's dislike of living near increasing shares of renters, a mechanism we explore in Section 6.2. Taken together, these results suggest that conditional on selecting ex-post more desirable Tracts, LTRs' entry and growth realize a smaller impact on prices than in the full sample of Tracts.

Before moving on to our results, we caveat that CoreLogic does not provide a balanced panel of Tracts with MLS listings; the sample of Tracts with available data increases over time. This means that the price and rent results are identified off different samples, both geographically and temporally. Appendix Figure D8(B) shows there is no statistically significant relationship between LTR share and entry into the MLS panel. This mitigates concerns that any differential sample selection is correlated with our endogenous variable.

Panel B of Table 4 presents the second-stage results, where the dependent variable is the

[27] Average local price growth (4.49 p.p. per year) added to the impact of a 1-σ above the mean increase in LTR share (1.82) $\implies$ 1.82/(4.49+1.82) = 0.29.

[28] A note on the sample limitations in Column (5): we condition on tracts with positive positive presence as of 2022. This means we exclude any Tracts in which LTRs entered and later exited before 2022, and do not use their price information in this estimation.

percent change in rents. In the full sample in Column (4), a 1 standard deviation increase in the instrumented annual change in LTRs' market share, $\Delta \widehat{LTRshare}_{it}$, increases the annual change of our MLS hedonic rent index by 0.803 p.p., but the effect is not statistically significant. A generous interpretation of the point estimate implies an annual elasticity of rent change with respect to LTR share of 2.72, which is much lower compared to the elasticity of house prices of 12.02 for the full sample in Panel A. It is noteworthy that our hedonic rent index constructed using MLS rental listings captures rental prices using a sample of only single-family homes and townhomes. This sample composition differs from other measures of market rents, such as the Zillow Observed Rent Index (ZORI), which includes all types of rental listings, including multi-family rentals.[29] ZORI may not capture the effects of LTRs on single-family rents alone if housing composition responded to LTR entry.

Moving to Tracts with positive 2022 LTR entry in Column (5), the point estimate falls to 0.081 and remains statistically insignificant. The implied elasticity is even lower at 0.275. Hence, in the intensive margin sample, LTRs do not measurably impact rents economically or statistically. In Column (6), we again observe little rent response by restricting the sample to Tracts with the highest LTR entries by 2022. The point estimate flips signs to become negative but remains statistically insignificant. The implied elasticity is -1.81. Overall, we found no evidence that LTRs meaningfully impacted rents between 2010 and 2022. In locations with higher LTR growth, the effects on rents seem to be smaller, potentially suggesting that the increase in rental supply put downward pressure on rents even as LTRs' market share rose. We discuss these potentially competing mechanisms in the next section.

Panel C of Table 4 presents the second-stage results, where the dependent variable is the change in the homeownership rate. In Column (4), a 1 standard deviation increase in the instrumented annual change in LTRs' market share, $\Delta \widehat{LTRshare}_{it}$, decreases the annual change in the homeownership rate by 0.526 p.p., statistically significant at the 1% level. For other drivers of homeownership, we observe a larger increase in Census Tracts with a more elastic housing supply, aligning with expectations. The point estimate implies an annual elasticity of homeownership change with respect to the LTR share of -2.96, meaning a 1 p.p. annual increase in LTRs' market share would induce a 2.96 p.p. (= 0.526 / 0.178) decrease in

[29]ZORI is only available from 2015 onwards. The ZORI utilizes a repeat-rent methodology to estimate mean listed rent in dollars, sampling from the 40th–60th percentiles of listed rentals, and using weights from the U.S. Census Bureau to reflect the composition of the underlying rental stock.

the homeownership rate. Alternatively, a Census Tract experiencing a 1 standard deviation above the mean change in LTR share would realize a 0.204 p.p. (= 0.026 + 0.178) annual change in LTR share, implying a 0.6 p.p. larger decrease in homeownership rate.

Column (5) focuses on the intensive margin of LTR share growth, excluding Tracts without LTR entry as of 2022. Here, the point estimate increases from -0.526 to -0.227, statistically significant at the 1% level. This estimate implies an annual elasticity of homeownership change with respect to LTR share of -1.28 (= -0.227/0.178), which is smaller in magnitude than in Column (4). For Tracts in this subsample experiencing a 1 standard deviation above the mean change in LTR share, the annual change in LTR share is 0.338 p.p. (= 0.08 + 0.258), leading to a 0.43 p.p. higher decrease in the homeownership rate.

Finally, in Column (6), which examines the top 10th percentile of Tracts by LTR entry as of 2022, the point estimate changes to -0.283 and is statistically significant at the 5% level. The implied elasticity of -1.59 is again smaller in magnitude than in Column (4) and comparable to Column (5). Collectively, these results suggest that in more ex-post desirable Tracts, LTR's entry exerts a smaller downward pressure on homeownership rate than in the full sample, likely driven by the fact that in these concentrated areas, there are fewer marginal homes available for them to buy year-over-year in our annual sample.

6 Heterogeneity and Potential Mechanisms

6.1 Industry Changes and Temporal Heterogeneity

As noted in Section 1, the single-family rental industry has gone through major changes over the past decade. Blackstone's 2012 Georgia foreclosure acquisitions birthed the industry. It experienced a major shift in late 2013 upon Invitation Homes' first public debt offering, which showed investors that purchasing cheap homes was not just a capital gains trade, but also yielded rental income. Finally, the COVID-19 pandemic saw a rapid search for space, with house prices growing too fast for many potential buyers with shallower funds than institutional players buoyed by a surge in ABS issuances (see Figure 1).

Figure 9 plots the results of splitting our regression into three time periods: the 2010-2014 industry birth, the 2015-2019 growth period after the first ABS issuance solidified the proof-of-concept, and the COVID-19 era characterized by the scramble for space a single-family

Table 4: OLS vs. IV Results

	(1) Full Sample	(2) Δ LTR ≥ 0%	(3) Δ LTR in Top 10pct	(4) Full Sample	(5) Δ LTR ≥ 0%	(6) Δ LTR in Top 10pct
	A. Prices					
	OLS			IV		
Z-score Δ LTR Share (Unit)	0.071***	0.055***	0.027**	1.575***	0.763***	0.687*
	(0.015)	(0.013)	(0.012)	(0.393)	(0.221)	(0.362)
Housing Supply Elasticity	-0.302***	-0.200*	-0.340***	-0.721***	-0.625***	-0.484***
	(0.065)	(0.112)	(0.077)	(0.078)	(0.164)	(0.164)
Observations	445,176	150,711	41,468	445,176	150,711	41,468
R-squared or RMSE	0.699	0.750	0.772	4.176	4.005	4.251
Dep. Var Mean (%)	4.486	5.282	6.064	4.486	5.282	6.064
Dep. Var S.D. (%)	7.192	7.740	8.355	7.192	7.740	8.355
Elasticity (%)				12.02	5.824	5.244
	B. Rents					
	OLS			IV		
Z-score Δ LTR Share (Unit)	-0.008	-0.009	0.022	0.803	0.081	-0.535
	(0.026)	(0.030)	(0.022)	(0.501)	(0.450)	(1.256)
Housing Supply Elasticity	-0.013	-0.060	-0.226	-0.186	-0.147	-0.228
	(0.081)	(0.087)	(0.140)	(0.115)	(0.100)	(0.248)
Observations	92,614	56,322	30,030	92,614	56,322	30,030
R-squared or RMSE	0.234	0.315	0.416	7.350	6.261	5.176
Dep. Var Mean (%)	4.807	4.953	5.137	4.807	4.953	5.137
Dep. Var S.D. (%)	8.546	7.697	6.830	8.546	7.697	6.830
Elasticity (%)				2.722	0.275	-1.814
	C. Homeownership					
	OLS			IV		
Z-score Δ LTR Share (Unit)	-0.025***	-0.025***	-0.022***	-0.526***	-0.227***	-0.283**
	(0.006)	(0.007)	(0.008)	(0.100)	(0.075)	(0.140)
Housing Supply Elasticity	0.067**	0.088**	0.101	0.144***	0.120***	0.126**
	(0.021)	(0.030)	(0.043)	(0.028)	(0.038)	(0.060)
Observations	818,313	272,563	96,638	818,313	272,563	96,638
R-squared or RMSE	0.039	0.052	0.066	3.471	3.565	3.793
Dep. Var Mean (%)	-0.182	-0.241	-0.321	-0.182	-0.241	-0.321
Dep. Var S.D. (%)	3.678	3.803	4.037	3.678	3.803	4.037
Elasticity (%)				-2.955	-1.275	-1.590

Notes: This table shows the second stage results for prices, rents, and homeownership. We control for Tract level house price elasticity of supply from Baum-Snow and Han (2024). All specifications include county-by-year fixed effects. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

home can provide. In each figure, the 2010-2014 coefficient reflects the baseline impact of LTRs on prices, rents, and homeownership; the 2015-2019 and 2020-2022 periods plot the difference relative to this baseline. Panel (A) shows the price results by era. Initially, increases in LTR market share did not move prices much. We posit a few reasons for this lack of price response. First, many LTRs buy with cash, drawing on non-mortgage sources of financing, and recent work has estimated a significant cash discount of around 11% (Reher and Volkanov, 2024). Second, early-stage LTRs purchased homes in substantial numbers out of foreclosure, leading to subsequent price indices incorporating this downward price pressure. These two mechanisms would then mitigate any upward price pressure being exerted by the LTRs. In unreported OLS estimates by period, we find positive, but statistically insignificant and economically much smaller impacts on prices during the first two periods, suggesting that positive selection on expected future returns drives the difference between the OLS and IV estimates. During the COVID-19 era, the choice set of available homes for LTR purchase had narrowed; no longer could LTRs buy homes out of foreclosure, nor could they accrue many properties at once. Thus, measurement error attenuates the OLS estimates, while positive selection declines, and our IV estimate is larger than the OLS.

As the industry grew, higher market shares translated to (insignificantly) lower house prices, perhaps due to the continuation of large investors buying with a cash discount, even as the stock of foreclosure purchases dwindled. During the COVID-19 era, prices rose more in areas with high increases in LTR shares, those with underlying product suitability for remote work and outdoor entertaining. These results suggest that, in the scramble for space during the COVID period, LTRs were willing to outbid significantly, perhaps expecting a permanent shift in demand for spacious rentals that would outlast the pandemic. This was prescient, as mortgage rates subsequently rose, leading households unable to transition to homeownership, yet in need of space. We note that other concurrent work also finds increasing prices rise on average, but do not examine the differential impact by period. Moreover, only Chang (2024) and Hanson (2024) use data prior to 2015, limiting the scope for work to study the birth of the industry, prior to the adoption of financing via ABS.

Panel (B) shows the temporal heterogeneity for rents. In the early period, rents fell as single-family supply began to expand, consistent with concurrent findings from Barbieri and Dobbels (2024); Chang (2024); Coven (2024) who cite increases in rental supply as well as better economies of scale relative to other landlords as mechanisms through which rents fall.

We exhibited rental supply expansion in Table 4, and documented falling management costs with respect to scale in Figure 7. Rents increased relative to this baseline in the growth period as rental demand grew (Mabille, 2023), but this did not put total upward pressure on rents. Finally, we see again that our main results are driven by the COVID-19 era. For a similar change in local demand (as proxied by county-by-year fixed effects), a Tract with a higher increase in the market share of LTRs realized a higher rise in rents. We posit that these differences may be driven by LTR's being more likely set rents using algorithms, which on average yield higher rental rates during times with increased demand (Calder-Wang and Kim, 2023).

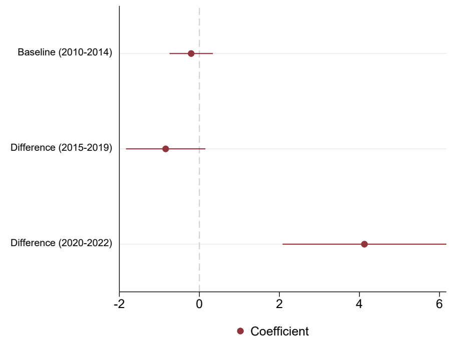
Panel (C) shows the heterogeneity results for homeownership. We see that the homeownership results are driven by declines in homeownership in both the early and later eras. In the early period, higher market share locations necessarily grew by cannibalizing owner-occupied housing much of which was foreclosed upon during the recession; no M&A activity was feasible yet, many home builders had collapsed during the Great Recession, and rental demand was strong for other landlord types. In the later period, higher market share growth locations again had to cannibalize the owner-occupant market as new construction came to a halt during the COVID-19 pandemic, leading to homeownership elasticity w.r.t. LTR share increase of -4.35, much higher than the elasticity of -1.78 for the baseline period.

In sum, LTR growth's impact on local housing markets varies by time depending on the state of the local housing market cycle, the state of the building industry, who the other market participants are, and their sources of funding.

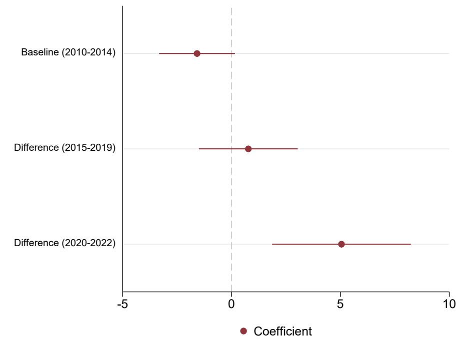
6.2 Potential Mechanisms

The results thus far suggest that increases in LTRs' local market shares meaningfully drive local house price increases, with more tenuous rent results. What is left undetermined is the underlying mechanisms. We consider three potential reallocation mechanisms. First, the implications of the *professionalization* of the landlord set, which reallocates properties from small to institutional landlords. Second, the implications of reallocating the single-family housing stock from owner-occupants to renters. Third, the reallocation of stock *within* the set of LTRs, which has been studied in the merger literature (Gurun et al., 2022; Austin, 2022). Fourth, the spillovers induced by rising renter market shares.

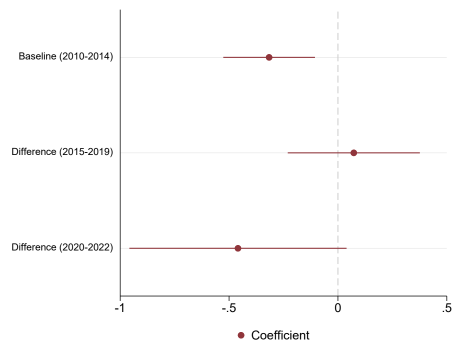
Figure 9: Heterogeneity by Period



(A) Prices



(B) Rents



(C) Homeownership

Notes: These figures show the differential impact of instrumented LTR market share on prices, rents, and homeownership by sample period. We divide the sample into three periods based on the industry's birth (2010-2014), its later growth (2015-2019), and the COVID-19 era characterized by large increases in the demand for residential space (2020-2022). We show the *baseline* 2SLS estimates for 2010-2014 in the top panel, and the *difference* in the 2SLS estimates for 2015-2019 and 2022-2022 relative to the baseline period in the middle and bottom panel respectively.

First, we walk through the implications of the *professionalization* mechanism. Calder-Wang and Kim (2023) find that adopting algorithmic pricing in rental markets leads landlords to extract more rents from tenants as they adjust prices more dynamically. This suggests that reallocating the rental stock from small to larger, more professionalized landlords could induce rent increases. This would then bid up prices for investor-owned properties as their net operating income increases through the adoption of OPMs which enable responsive pricing and lower management costs. The overall impact on rents is ambiguous; on the one hand, responsive pricing tends to raise rents on average as in Calder-Wang and Kim (2023), but falling management costs would concurrently put downward pressure on rents.

The second source of reallocation induced by the rise of LTRs is the *reallocation* of the rental stock from owner-occupants to renter-occupants. This has been documented in the data as a rising share of investors owning the single-family housing stock (Lambie-Hanson et al., 2022). This shifts the supply curve in for owner-occupants, and out for renter-occupants, inducing price increases and rent decreases.

Third, once LTRs have established meaningful market shares by having already obtained portfolios from smaller landlords or owner-occupants, they begin to *merge and acquire* each other. Gurun et al. (2022) use three mergers occurring between December 2015 and November 2017; Austin (2022) uses the same three mergers as Gurun et al. (2022), adding in the acquisition of Silver Bay Realty Trust by Tricon Residential in mid-2017. Both papers find small increases in prices and rents in neighborhoods with increased market share.

Fourth, once LTRs move into a location, they change the mix of stakeholders and associated *amenities*. For example, (Gurun et al., 2022) finds that large landlords in charge of local amenities lower crime, which raises rents. On the other hand, Billings and Soliman (2023) finds under-maintenance of rental properties puts downward pressure on neighboring prices. Overall, the impact of increased rental shares depends on the quality of neighborhood maintenance, and hence, the quality of the landlord *relative* to the local homeowners. Another area of tension between renters and homeowners as of yet unexplored is the potential for amenity mismatch, which could also lead to lower prices.

A final mechanism we leave for future research is the impact of the nascent build-to-rent industry; we do not have a very long time period or many homes to study their impact at this point. This industry took off during the COVID-19 pandemic, as households moved to suburbs and exurbs seeking space. As renters moved towards more elastically supplied locations, builders began working with LTRs to provide portfolios of homogeneous single-family rentals. Increasing single-family build-to-rent would expand the rental supply further, putting downward pressure on rents, and holding quality fixed. Taken together, these mechanisms (excluding build-to-rent) point to a series of testable hypotheses we take to the data, by comparing different types of transitions between owners, as summarized in Table 5.

To test these hypotheses, we identify how units transition between different types of owners, as shown in Table 6. The table breaks down sellers from which LTRs buy, and to whom they sell. We see that LTRs buy a little more than 701k single-family and townhome

Table 5: Mechanism & Hypotheses Summary

	Prices	**Rents**	**Transition**
Professionalization	$\uparrow$	$\sim$	SLLs $\rightarrow$ LTRs
Tenure Reallocation	$\uparrow$	$\downarrow$	Owner-Occupants $\rightarrow$ LTRs
M & A	$\uparrow$	$\uparrow$	LTRs $\rightarrow$ LTRs
Amenities	$\sim$	$\sim$	(Owner-Occupants + Speculators) $\rightarrow$ LTRs

units, and sell approximately 311k units, netting to a gain of nearly 390k homes.[30] LTRs buy 46% of their units from owner-occupants, as owner-occupants own most single-family and townhome units. Buying from speculators in large amounts also makes sense as these investors are profit-motivated and grew rapidly during the last housing cycle prior to the Great Recession (Bayer et al., 2020). LTRs rarely buy from other small landlords, potentially as rents and renter demand increased over this period, leading small landlords to hold on to their properties. Lastly, LTRs acquire 29% of their units from each other; this market has been a hotbed of mergers, acquisitions, IPOs, spin-offs, and privatization.

Table 6: Buyer-Seller Transition Matrix

	Other Investor	SLLs	LTRs	iBuyers	Builders	Speculators	Owner Occupants	Total
LTRs Buy from:	19,125	53,861	200,741	3,923	5,915	98,433	319,010	701,008
% from each	2.73	**7.68**	**28.64**	0.56	0.84	**14.04**	**45.51**	100.00
LTRs Sell to:	4,844	20,753	200,741	73	1,115	15,235	68,492	311,253
% from each	1.56	6.67	**64.49**	0.02	0.36	4.89	22.01	100.00

Notes: This table shows the transactions made by LTRs, characterized by the investor on the other side of the trade: Other Investors, SLLs, LTRs, iBuyers, Speculators, and Owner Occupants. Data from CoreLogic Deeds 2010-2022, investor types authors' definitions.

On the sell side, LTRs sold about one-fifth of their properties back to owner-occupants, with much of this activity occurring during the desperate scramble for space during the COVID-19 pandemic. The remaining bulk of their sales go to other LTRs. This highlights that once a unit becomes a single-family rental property, it is near-absorbing, with nearly two-thirds of LTR sales to other LTRs again through mergers or acquisitions.

This transition matrix guides our hypotheses tests above. We can test the *profession-*

[30] Our summation of net purchase activity differs from the 415k in total holdings in Section 3 for two reasons. First, there was some activity among the set of 58 LTRs prior to 2010. We estimate these firms held 18,346 units in 2009. Second, we cannot observe the identity of the other party in about 7,500 LTR transactions, making it impossible to classify the transition type.

alization channel by studying units sold by SLLs to LTRs; the *supply* channel using units sold by owner occupants or speculators to LTRs; the *concentration* channel by transactions between LTRs; and the *spillovers* channel by the rise in rental shares. To instrumentalize these tests, we first measure how much LTRs buy on the net from each investor type, g, in each Tract, i between 2010 and 2022:

$$NetSales_i^g = (Transactions_i^{g \to LTR}) - (Transactions_i^{LTR \to g}) \tag{10}$$

$\forall g \in \{OwnerOccupants, SmallLandlords, Speculators\}$. We then identify which Tracts have the largest net purchases from each group:

$$Top_i^g = \left(\frac{NetSales_i^g}{SFTH_i^{2010}} \geq p^{95} \right) \tag{11}$$

where i indexes Tracts, $SFTH_i^{2010}$ is the initial stock of single-family and townhome units in a Tract in 2010 to control for potential market size, and p^{95} is the 95^{th} percentile of each fraction's distribution. Equation 11 indicates whether a Tract had right-tail reallocation between an investor type and LTRs. This definition is 0 when calculating sales between LTRs; instead, we use the number of LTRs active in a given Tract each year, $ActiveLTR_{it}$.

We estimate the following horserace regression specification by interacting the annual changes in LTRs' market share, $\Delta LTRshare_{it}$ and the annual changes in the instrument, ΔIV_{it}, with the set dummies, Top_i^g's and the number of active LTRs, $ActiveLTR_{it}$:

$$\textit{First Stage}: \qquad \boldsymbol{X} = \boldsymbol{Z\Pi} + \boldsymbol{W\Gamma} + \boldsymbol{\epsilon}, \tag{12}$$

$$\textit{Second Stage}: \boldsymbol{\Delta Y} = \hat{\boldsymbol{X}}\boldsymbol{\beta} + \boldsymbol{W\delta} + \tilde{\boldsymbol{\varepsilon}}, \tag{13}$$

where $\boldsymbol{X} = \begin{pmatrix} \Delta LTRshare_{it}, \Delta LTRshare_{it} \times Top_i^{OO}, \Delta LTRshare_{it} \times Top_i^{SLL}, \\ \Delta LTRshare_{it} \times Top_i^{Spec}, \Delta LTRshare_{it} \times ActiveLTR_{it} \end{pmatrix}$ is the matrix of endogenous regressors, $\boldsymbol{Z} = \begin{pmatrix} \Delta IV_{it}, \Delta IV_{it} \times Top_i^{OO}, \Delta IV_{it} \times Top_i^{SLL}, \\ \Delta IV_{it} \times Top_i^{Spec}, \Delta IV_{it} \times ActiveLTR_{it} \end{pmatrix}$ is the matrix of instrumental variables, $\boldsymbol{W} = (\boldsymbol{W}_{it}, \delta_{ct})$ is the matrix of control variables which include the housing supply elasticity at the Tract level and county-by-year fixed effects as in Equations 7 and 8, and $\hat{\boldsymbol{X}} = \boldsymbol{Z}\hat{\boldsymbol{\Pi}} + \boldsymbol{W}\hat{\boldsymbol{\Gamma}}$ is the fitted values from the first stage. $\boldsymbol{\beta}$ is the vector of second-stage coefficients. The coefficients for the interaction terms in $\boldsymbol{X}$ capture the differential effects in the set of Tracts where LTRs reallocate the most from owner-occupants, small landlords, and speculators, and where more than one active LTRs are operating, relative to a baseline group of Tracts where there is exactly one active LTR and sellers are not concentrated by type.

Figure 10 shows the results of estimating the horserace regression in Equation 12 and 13. Panel (A) shows how prices respond to different types of reallocations. First, prices fall when a large stock of units is transferred from small landlords to LTRs, attenuating the baseline price increases by 12%. This goes against the professionalization story as the main local impact driving prices. Prices fall even more when units are diverted from speculators or owner-occupants. In Tracts with the top 5% transfer shares from owner-occupants to LTRs, the plotted coefficient offsets 85% of the baseline price impact, and top speculator transfer Tracts lower the baseline price impact by 29%. These results suggest that the negative spillovers induced by increased rental shares drive down prices significantly. Panel (B) shows the same reallocation horserace but for rents. Rents do not seem to differ when units move in large quantities from small to professional landlords. This suggests that the falling management costs may offset the rent increases by using automated rent algorithms. There is strong support for the supply channel, with rents falling in areas with significant reallocation from speculators, who often hold homes vacant, and owner-occupants (though only the speculator results are statistically significant at the 95% level).

Contrary to the merger literature, we do not find much evidence in support of the concentration channel; additional LTRs do not seem to move prices or rents much relative to our baseline estimates, highlighting the fact that identification using a select group of mergers may only teach us about a unique set of neighborhoods. This is consistent with even the 99^{th} percentile Tract having a market share of 9%, a much lower threshold than would be traditionally identified as a concentrated market.

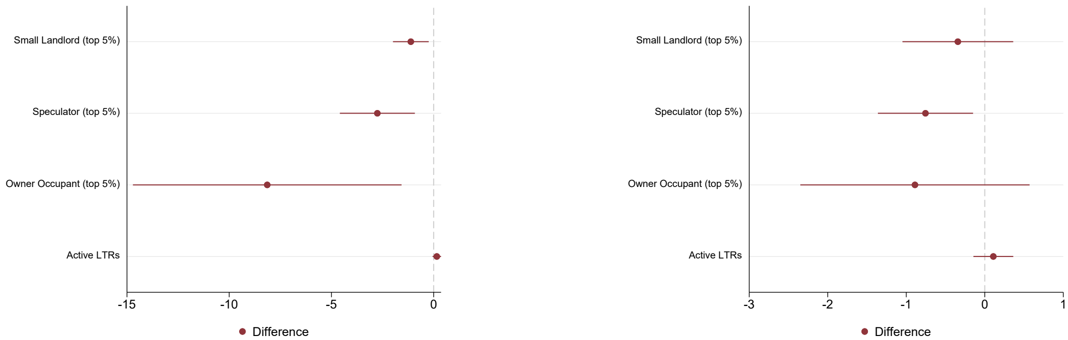
Instead of relying on regression analysis, we can directly measure the LTR-implied homeownership rate changes. In the 2010 Census, there were 65,779,696 owner-occupied attached and detached single-family units, the closest definition to our CoreLogic sample of single-family and townhome units. Renters occupied 13,301,120 attached and detached single-family units in 2010, for a total occupied housing stock of 79,080,816 units. This yields a homeownership rate of 83.18%. Accounting for a 13% vacancy rate, as provided by the 2010 American Community Survey, yields 11,921,273 more single-family and townhome units.

We calculate the change in homeownership by summing up the net sales between LTRs and other owners, but must make some assumptions on the occupancy status for units held by certain investors. First, we noted that we are uncertain how investors holding fewer than 2 units use their homes. These could be vacation properties, spare units for visitors, or rented out. Second, we are uncertain about the vacancy rates of homes owned by speculators. If speculators value ease of transacting and liquidity, they may keep these units vacant as many states protect tenants from being evicted prior to their lease end, even in the case of sale. Due to these ambiguities, we bound our homeownership change estimates by assuming zero or full occupancy in these units. Finally, since iBuyers purchased 92% of their units from owner-occupants, and their business model is to turn properties around in a few months, we treat transitions from iBuyers to LTRs as moving units from owner- to renter-occupancy.

Assuming other investors and speculators rent out all of their units, we only see a change in tenure for transactions between LTRs, builders, iBuyers, and owner-occupants. Buying from iBuyers and owner-occupants transitions units from owner-occupancy to rentals, while buying from builders adds directly to the rental stock. Summing up the net sales between these four types with the rental stock in 2010 yields a 2022 rental-occupied stock of 13,559,980, up about 260k units. Removing the LTR net purchases from the owner-occupied stock in 2010 lowers the unit count by 250.5k units, for a total of 65,529,178 owner-occupied units. This yields a homeownership rate of 82.85%. Assuming that all other investors and speculators kept their properties vacant increases the total stock of housing units in the denominator by 97,479 units, and lowers the homeownership rate further to 82.75%. This leads to an LTR-induced decline in homeownership of 0.33-0.43% nationally.

We can decompose the relative contributions of the change in homeownership attributable to the decline in owner-occupancy (transfers from owner occupants or iBuyers) vs. the decline in vacancies in the full-vacancy assumption case. The change from declines in the owner-occupied stock can be calculated as the change in the number of owner-occupied units, relative to the total occupied housing stock in 2010: -0.32%. We calculate change from lowering vacancies as the difference between the 2010 homeownership rate and the homeownership rate using the 2010 owner-occupied units and the 2022 occupied housing stock, which incorporates those units now for lease by the LTRs that had been vacant when owned by other investors and speculators: -0.11%. Taken together, transitions from owner→renter accounted for 74% of the decline in homeownership, while transitions from vacancies→renter comprised 26% of the decline. In reality, some share of units owned by other occupants and

Figure 10: Net Sale Heterogeneity



(A) Prices **(B)** Rents

Notes: These figures show the differential impact of instrumented LTR market share on prices, rents, and homeownership by transaction type. We characterize census Tracts as having high or low shares of transactions net-bought by LTRs and net-sold by small landlords, speculators, or owner-occupants. Because this measure is not feasible between LTRs, we instead count the number of active LTRs in a given Tract to proxy for local industry competition.

speculators may have been rented out, suggesting that the true owner→renter transition explains between 74 and 100% of the decline in homeownership attributable to LTRs.

To gauge the magnitude of the decline in homeownership attributable to LTRs, it is useful to note that over the era of study, overall homeownership rates in the U.S. fell from 67.1% in 2010 to 66.0% in 2022. For single-family (detached and attached) homes, it actually rose from 83.18% to 84.07%, likely as most single-family production was built-to-sell, rather than the more modern rise of build-to-rent.[31] While a 0.32% impact may initially seem small, it is meaningful relative to long-run and slow-moving trends in homeownership rates, potentially explaining a large amount of media and policymaker focus.

7 Discussion and Further Work

Our findings suggest that the rise of LTRs and the single-family rental market has had, on average, modest effects on local housing markets. Prices rise, rents remain roughly the same, and homeownership falls moderately. In this section, we highlight two areas of active

[31] U.S. Census Bureau, Homeownership Rate in the United States [RHORUSQ156N], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/RHORUSQ156N, January 31, 2025. Single-family results from 2022 ACS, authors' own calculations

research that the rise in LTRs can inform: public policy aimed at enabling households to consume housing where they wish, and the lack of integration in rental markets.

7.1 "Moving to Opportunity" vs. First Time Homebuyers

It is natural to ask how the rise of this industry impacts potential neighborhood entrants. For entrants, the rise of single-family rentals has created opportunities for renting in better locations but has made buying a home more difficult. This creates a private sector laboratory that can shed light on the trade-off between two popular public housing policies: moving to opportunity and supporting first-time homebuyers. Concurrent work has found that rising prices make it more difficult for potential homebuyers (Barbieri and Dobbels, 2024), unsurprising given the cash advantage of the LTRs combined with their upward pressure on prices documented above. As of yet, we are unaware of work that studies the trade-off in welfare between these two groups: potential renters who benefit, and potential homebuyers who suffer. We leave it to future work to study the net impact and its aggregate implications.

Other new entrants, the renters, tend to move from less upwardly mobile locations (Coven, 2024). As a review, the Move-to-Opportunity program of the 1990s offered a few thousand families living in high-poverty areas housing vouchers to move to areas with higher socio-economic status, or more "opportunity." The experiment intended to study whether taking children out of high-poverty locations and relocating them to low-poverty locations lead to better educational and employment outcomes later in life. Results of these experiments have been mixed, with education and employment outcomes dependent on the age of children when they move (Chetty et al., 2016); however, adults generally reported having better mental health and feeling safer in their neighborhoods. Even given these positive outcomes, low-income residents seem not to select opportunity-rich neighborhoods, largely driven by the difficulty in searching for available housing (Bergman et al., 2024).

LTRs' expansion of rental supply in middle-class, single-family neighborhoods cannot replicate the MTO experiment but demonstrates that some gains to affordability can be achieved in the private sector. However, as in Derenoncourt (2022), our findings highlight the limitations of improving affordability in locations of opportunity on a larger scale: locations are not static. General equilibrium effects mean that the characteristics that make a location "high opportunity," namely the incumbents and their curated amenity sets, respond to inflows of new types of residents. The observed improvements in rental supply and lower rental prices may be beneficial in the short run, allowing large numbers of families to access better neighborhoods, but longer-term responses may attenuate these benefits. Given the sensitivity of prices and rents to as-of-yet fairly small changes in the homeownership rate, and that in-migrants are not impoverished (they still have to afford private sector rents on three-bedroom homes in middle-class areas) we posit that scaling up programs like MTO may have limited effectiveness once neighborhoods respond.

7.2 LTRs and Rental Market Segmentation

Recent work by Greenwald and Guren (2024) study whether credit conditions move house prices. The existing literature differs in its conclusions, largely based on whether the rental market is assumed to be *fully segmented* or *fully integrated*. In the segmented model, often assumed in micro-housing models, the housing market has a fixed homeownership rate. Intuitively, this means that owner-occupied houses tend to remain owner-occupied, no matter the credit conditions. Changes in credit supply thus tend to move house *prices*. On the other hand, in integrated markets, common in the macro-housing literature, landlords with deep pockets transition units between owner-occupancy and rental-occupancy. Landlord demand supports prices when credit supply dries up for potential owner-occupants, and landlords sell rental units to owner-occupants as credit conditions improve. As a result, in integrated markets, credit conditions change *homeownership rates*. Greenwald and Guren (2024) work to reconcile these findings and provide a measure of the *degree* to which markets are segmented or integrated. They find evidence that housing markets in the US are much closer to full segmentation than integration.

This paper shows that LTRs reallocate housing from owner-occupants to rentals over a period characterized by tight credit conditions (Mabille, 2023). These LTRs act exactly as the deep-pocketed investors would in the *fully integrated* world rejected by Greenwald and Guren (2024). If the single-family rental industry continues to expand, and interest rates remain high, we may see increasing integration in this particular market segment, though we haven't yet seen whether these LTRs exit once credit conditions improve. Working against improvements in integration is the fact that LTRs sell to each other 70% of the time, and to owner-occupants less than 20% of the time. We leave it to future research to examine whether these LTRs have increased integration, noting that this is likely difficult as we have not experienced major improvements in credit conditions for potential homebuyers.

8 Conclusion

Media and policymakers often characterize LTRs as a new type of villainous landlord. However, our results support their role in supply expansion more than in price-setting, suggesting that declining rents are the bigger story than rising prices. Using comprehensive housing deed records from 2010 to 2022, we document the rapid expansion of Long-Term Rental (LTR) companies, including private equity-backed real estate firms and publicly traded institutional landlords. These companies have outpaced other investor types, such as builders and iBuyers, strategically concentrating their holdings to expand local market shares. Unlike traditional small landlords (SLLs), LTRs predominantly target newer, mid-sized single-family homes in neighborhoods characterized by strong rental demand, low vacancy rates, and high minority shares, raising concerns about potential gentrification effects.

Our empirical analysis indicates that increases in LTRs' local market shares drive up local house prices while reducing homeownership, with rents showing mixed effects. A one-standard-deviation increase in LTR share leads to a 1.58 p.p. rise in house prices and a 0.53 p.p. decline in homeownership, with no significant effect on rents in the aggregate. However, heterogeneity tests reveal that reallocations from owner-occupants and speculators to LTRs tend to lower prices due to negative spillover effects from rising rental shares. Moreover, rents decrease in areas where LTRs acquire properties from speculators, who often keep homes vacant, and from owner-occupants, consistent with a supply expansion mechanism.

Our findings underscore the evolving role of institutional landlords in housing markets and its implications for affordability, homeownership, and neighborhood composition. While LTRs may expand rental options, their concentration and market influence reshape tenure dynamics and local property values. These effects were particularly pronounced during the COVID-19 period when demand for single-family rentals surged. Our results highlight the need for continued examination of the interactions between institutional landlords, housing affordability, and neighborhood stability in the evolving housing market landscape.

References

M. T. Allen, J. Rutherford, R. Rutherford, and A. Yavas. Impact of investors in distressed housing markets. *The Journal of Real Estate Finance and Economics*, 56:622–652, 2018.

B. Y. An, A. Jakabovics, A. W. Orlando, S. Rodnyansky, and E. Son. Who owns america? a methodology for identifying landlords' ownership scale and the implications for targeted code enforcement. *Journal of the American Planning Association*, pages 1–15, 2024.

N. Austin. Keeping up with the Blackstones: Institutional investors and gentrification. *Working Paper*, 2022.

C. Badarinza and T. Ramadorai. Home away from home? foreign demand and london house prices. *Journal of Financial Economics*, 130(3):532–555, 2018.

F. Barbieri and G. Dobbels. Market power and the welfare effects of institutional landlords. *Working Paper*, 2024.

T. Bartik. *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute., 1991.

N. Baum-Snow and L. Han. The microgeography of housing supply. *Journal of Political Economy*, 132(6):1897–1946, 2024.

P. Bayer, C. Geissler, K. Magnum, and J. W. Roberts. Speculators and middlemen: The strategy and performance of investors in the housing market. *Review of Financial Studies*, 33:5212–5247, 2020.

P. Bayer, K. Mangum, and J. W. Roberts. Speculative fever: Investor contagion in the housing boom. *American Economic Review*, 111:605–651, 2021.

P. Bergman, R. C. Chetty, S. DeLuca, N. Hendren, L. F. Katz, and C. Palmer. Creating moves to opportunity: Experimental evidence on barriers to neighborhood choice. *American Economic Review*, 114:1281–1337, 2024.

S. B. Billings and A. Soliman. The erosian of homeownership and minority wealth. *Working Paper*, 2023.

O. J. Blanchard and L. F. Katz. Regional evolutions. *Brookings Papers on Economic Activity*, 1:1–75, 1992.

G. Buchak, g. Matvos, T. Piskorski, and A. Seru. Why is intermediating houses so difficult? evidence from iBuyers. *NBER Working Paper Series No. 28252*, 2022.

S. Calder-Wang and G. H. Kim. Coordinated vs efficient prices: The impact of algorithmic pricing on multifamily rental markets. *Working Paper*, 2023.

K. Chang. Diversifying the suburbs: Rental supply and spatial inequality. *Working Paper*, 2024.

R. Chetty, N. Hendren, and L. F. Katz. The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, 106:855–902, 2016.

A. Chinco and C. Mayer. Misinformed speculators and mispricing in the housing market. *The Review of Financial Studies*, 29(2):486–522, 2016.

B. Christophers. How and why u.s. single-family housing became an investor asset class. *Journal of Urban History*, 49:430–449, 2023.

J. Coven. The impact of institutional investors on homeownership and neighborhood access. *Working Paper*, 2024.

D. Cvijanoviĉ and C. Spaenjers. We'll always have paris: Out-of-country buyers in the housing market. *Management Science*, 67(7):4193–4213, 2021.

M. A. Davis, A. Ghent, and J. Gregory. The work-from-home technology boon and its consequences (with morris a. davis and jesse gregory. *Review of Economic Studies*, 91: 3362–3401, 2024.

A. A. DeFusco, C. G. Nathanson, and E. Zwick. Speculative fever: Investor contagion in the housing boom. *Journal of Financial Economics*, 146:205–229, 2022.

A. Demers and A. L. Eisfeldt. Total returns to single-family rentals. *Real Estate Economics*, 50:7–32, 2021.

E. Derenoncourt. Can you move to opportunity? Evidence from the Great Migration. *American Economic Review*, 112:369–408, 2022.

R. Diamond and T. McQuade. Who wants affordable housing in their backyard? an equilibrium analysis of low-income property development. *Journal of Political Economy*, 127 (3):1063–1117, 2019.

Y. Elster, I. Ater, and E. B. Hoffman. Real-estate investors, house prices and rents: Evidence from capital-gains tax changes. *Maurice Falk Institute for Economic Research in Israel. Discussion paper series*, 2021.

J. Favilukis and S. van Nieuwerburgh. Out-of-town home buyers and city welfare. *Journal of Finance*, 76(5):2577–2638, 2021.

C. Garriga, P. Gete, and A. Tsouderou. The economic effects of real estate investors. *Real Estate Economics*, 51:655–685, 2023.

K. Gerardi, E. Rosenblatt, P. S. Willen, and V. Yao. Foreclosure externalities: New evidence. *Journal of Urban Economics*, 87:42–56, 2015.

M. Giacoletti, R. Heimer, W. Li, and E. G. Yu. Single-family reits and local housing markets. *Working Paper*, 2024.

P. Goldsmith-Pinkham, I. Sorkin, and H. Swift. Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624, 2020.

L. Goodman, A. Zinn, K. Reynolds, and O. Noble. A profile of institutional investor-owned single-family rental properties. Technical report, The Urban Institute, 2023.

C. S. Gorback and B. J. Keys. Global capital and local assets: House prices, quantities, and elasticities. *NBER Working Paper*, No. 27370, 2020.

D. L. Greenwald and A. Guren. Do credit conditions move house prices? *Working Paper*, 2024.

A. Gupta. Foreclosure contagion and the neighborhood spillover effects of mortgage defaults. *The Journal of Finance*, 74:2249–2301, 2019.

A. Gupta, J. Coven, and I. Yao. Jue insight: Urban flight seeded the covid-19 pandemic across the united states. *Journal of Urban Economics*, 133, 2023.

U. G. Gurun, J. Wu, S. C. Xiao, and S. W. Xiao. Do wall street landlords undermine renters' welfare? *The Review of Financial Studies*, 36:70–121, 2022.

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

A. Harrison, D. Immergluck, and J. Walker. Single-family rental (sfr) investor types, property conditions, and implications for urban neighbourhoods: evidence from memphis, tennessee. *Housing Studies*, pages 1–21, 2024.

L. Lambie-Hanson, W. Li, and M. Slonkosky. Real estate investors and the U.S. housing recovery. *Real Estate Economics*, 50:1425–1461, 2022.

K. Lee and D. Wylie. Institutional investors, rents, and neighborhood change in the single family residential market. *Working Paper*, 2024.

A. Levy. Housing policy with home-biased landlords: Evidence from french rental markets. *Working Paper*, 2022.

P. Mabille. The missing homebuyers: Regional heterogeneity and credit contractions. *Review of Financial Studies*, 36:2756–2796, 2023.

A. Mian and A. Sufi. Credit supply and housing speculation. *Review of Financial Studies*, 35:680–719, 2022.

J. Mills, R. Molloy, and R. Zarutskie. Large-scale buy-to-rent investors in the single-family housing market: The emergence of a new asset class. *Real Estate Economics*, 47:399–430, 2022.

F. Qian and R. Tan. The effects of high-skilled firm entry on incumbent residents. *Stanford Institute for Economic Policy Research (SIEPR) Working Paper*, (21-039), 2021. doi: 10.2139/ssrn.3982760. URL https://ssrn.com/abstract=3982760.

L. Quintero. Fewer players, fewer homes: Concentration and the new dynamics of housing supply. *Working Paper*, 2023.

M. Reher and R. Volkanov. The mortgage-cash premium puzzle. *The Journal of Finance*, 79, 2024.

J. Rutherford, R. Rutherford, A. Yavas, L. Wedge, and M. T. Allen. Micro evidence relating to house rents, prices and investor size from a matched dataset. *The journal of real estate finance and economics*, pages 1–27, 2023.

INTERNET APPENDIX

A Data Construction Appendix

A.1 Ownership Imputation: A Real (Anonymized) Example

We provide a real (anonymized) example of the ownership imputation process. Table A1 documents the property's transaction history: it was first sold in 2002 from the original owner (Anonymous 1) to two buyers (Anonymous 2 Cosigner) and later transferred again in 2016 to new owners (Anonymous 3 Cosigner B). Table A2 presents the imputed ownership from 2000 to 2022. Based on our imputation, Anonymous 1 owned the property from 2000 to 2001, Anonymous 2 Cosigner from 2002 to 2015, and Anonymous 3 Cosigner B from 2016 to 2022. While ownership could be imputed at a monthly level, we assign ownership at year-end to streamline our analysis.

Table A1: Transaction Records

Year	Seller	Buyer
2002	Anonymous 1	Anonymous 2 & Cosigner
2016	Anonymous 2 & Cosigner A	Anonymous 3 & Cosigner B

A.2 Identifying Subsidiaries of Publicly-Listed and Private Firms

We develop a novel process to identify subsidiaries of large investors by scraping SEC 10-K filings, reviewing public company records from OpenCorporates, and analyzing industry reports. We consolidate the property holdings of these subsidiaries under their respective parent companies. For large publicly traded firms, we manually collect subsidiary names reported in each year's 10-K filings, a critical step since many subsidiaries have names that do not resemble their parent company.

For example, Table A5 presents Invitation Homes, whose subsidiaries — identified from 10-K filings and public company records — include entities such as *"INVITATION HOMES LLC", "014-1 IH EQUITY OWNER LP", and "IH2 PROPERTY NORTH CA LP"*. To

Table A2: Imputed Ownership

Year	Owner
2000	Anonymous 1
2001	Anonymous 1
2002	Anonymous 2 & Cosigner A
2003	Anonymous 2 & Cosigner A
2004	Anonymous 2 & Cosigner A
2005	Anonymous 2 & Cosigner A
2006	Anonymous 2 & Cosigner A
2007	Anonymous 2 & Cosigner A
2008	Anonymous 2 & Cosigner A
2009	Anonymous 2 & Cosigner A
2010	Anonymous 2 & Cosigner A
2011	Anonymous 2 & Cosigner A
2012	Anonymous 2 & Cosigner A
2013	Anonymous 2 & Cosigner A
2014	Anonymous 2 & Cosigner A
2015	Anonymous 2 & Cosigner A
2016	Anonymous 3 & Cosigner B
2017	Anonymous 3 & Cosigner B
2018	Anonymous 3 & Cosigner B
2019	Anonymous 3 & Cosigner B
2020	Anonymous 3 & Cosigner B
2021	Anonymous 3 & Cosigner B
2022	Anonymous 3 & Cosigner B

systematically classify these entities, we extract key strings from subsidiary names and incorporate them into regular expression criteria, enabling us to identify and consolidate all subsidiary holdings under the unified parent name, “Invitation Homes”.

For private firms, that lack publicly available subsidiary disclosures, we mainly rely on public company records from OpenCorporates to identify their subsidiaries. Table A6 provides examples of parent companies, relevant keywords, and their corresponding subsidiaries.

Table A3: Examples of Subsidiaries of Public Firms

Number	Parent Company	Keywords	Subsidiary Company
1	Invitation Homes	invitation homes, ih equity, ih borrower, ih property, IHE BORROWER, 1H BORROWER, I H BORROWER, ...	INVITATION HOMES LLC..., 2014-1 IH EQUITY OWNER LP..., 2019-1 IH BORROWER LP..., IH2 PROPERTY NORTH CA LP..., 2013-1 IHE BORROWER LP..., 2018-2 1H BORROWER LP..., 2018-2 I H BORROWER..., ...
2	American Homes 4 Rent	amh, ah4r, AMEICAN HMS 4 RENT, A M H, AMER HOMES 4 RENT, AMERICAN HOMES 4 REN, ...	AMH 04 BORROWER LLC..., AH4R PROPERTIES-AP LLC..., AMEICAN HMS 4 RENT PROPS TEN L..., A M H INC..., AMER HOMES 4 RENT LLC..., AMERICAN HOMES 4 REN PROP 7LLC..., ...
3	VineBrook Homes	VINEBROOK	VINEBROOK ANNEX B LLC, 2 VINEBROOK ROAD REALTY TRUST, VINEBROOK PROPERTIES LLC, ...
4	Carlyle Group	ALP, AMC, APOLLO AVIATION, ASCP, ASP, BETACOM, CARLYLE, CDL, CECP, CELF, CEP, CER, CGP.	ALP HOLDING LLC..., AMC & EM PROPERTIES LLC..., APOLLO AVIATION LLC..., ASCP II LLC..., ALPHA FAM ASP LLC..., BETACOM INC..., CARLYLE & ASSOC INC CO..., CDL CONSTRUCTION LLC..., CECP ENTS LLC..., CELF LLC..., CEP CONSTRUCTION LLC..., CER DEV CORP..., CGP FAMILY LP...
...	...	...	...

Table A4: Examples of Subsidiaries of Private Firms

Number	Parent Company	Keywords	Subsidiary Company
1	Progress Residential	PROGRESS RES, PROGRESS R, PROGRESS RESIDENTIAL.	PROGRESS RES BORROWER 1 LLC..., PROGRESS R BORROWER 17 LLC..., PROGRESS RESIDENTIAL 2 LLC...
2	FirstKey Homes	FIRST KEY, FIRSTKEY HOME, FKH.	FIRST KEY HOMES INC..., FIRSTKEY HOMES LLC..., FKH SFR PROPCO G FIRSTKEY HOMES LLC...
3	Tricon Residential	TRICON, TRI-CON.	TRICON BUILDERS INC..., TRI-CON CONST CORP...
4	Home Partners of America	HPA, HOME PARTNERS.	HPA ESTATES LLC..., HOME PARTNERS HOLD CO LLC...
...	...	...	...

B Chat GPT Prompt

To prevent over-aggregation of portfolios with common names (e.g., "John Smith"), we designed a prompt for ChatGPT instructing it to classify 10.3 million investor names as individual-like or corporate-like. We provide the prompt below in full, with the exception that we anonymized all entity and individual names used to provide guidance. Following receipt of ChatGPT's output, we manually checked a random sample of names to ensure these matched our expectations.

ChatGPT Prompt (Anonymized)

Analyze the given name and determine if it contains a complete personal name.
Instructions:

1. A complete personal name includes both a first and last name and may contain initials.

2. The given name can be:

   – Pure personal name(s).
   – Personal name(s) with an organization suffix.
   – Pure business name(s)
   – Business name(s) with an organization suffix.

3. If the name contains a complete personal name or multiple complete personal names, remove any organization suffix and output "1 (the personal name(s))"; otherwise, output "0".

Note: Recognize various institutional suffixes (e.g., TRUST, TRST, LLC, LP, CORP, PARTNERSHIP, etc., and their abbreviations) to avoid incorrectly including them as part of a person's name. Additionally, account for organizational suffixes consisting of more than one phrase (e.g., LIVING TRUST, HOMES LLC, etc.).

Example:

– Input: "LASTNAME FIRSTNAME""
– Output: "1 (LASTNAME FIRSTNAME)"

– Input: "BUSINESSNAME1"
– Output: "0"

– Input: "LASTNAME FIRSTNAME1 FIRSTNAME2 MIDDLENAME"
– Output: "1 (LASTNAME FIRSTNAME1 FIRSTNAME2 MIDDLENAME)"

– Input: "BUSINESSNAME2 LLC"
– Output: "0"

⋮

– Input: "LASTNAME INITIAL INITIAL INITIAL LIVING T"
– Output: "1 (LASTNAME INITIAL INITIAL INITIAL)"

C Appendix Tables

Table C1: LTR Market Presence as of 2022

Among	Median Across Tracts	Nationally
	Ownership Share as of 2022	
All Housing Units (ACS)	0.21%	0.29%
Single Family & Townhome (SFTH) Units (ACS)	0.32%	0.43%
Renter-Occupied SFTH (ACS)	2.38%	2.85%
	Transaction Share 2010–2022	
LTR purchases/all SFTH transactions	9.09%	4.88%
LTR sales/all SFTH transactions	12.5%	2.10%
(LTR purchases+sales)/all SFTH transactions	15.8%	6.98%

Notes: Median conditional on positive market presence. Data on total housing stock, total single-family and townhome units (SFTH), and total renter-occupied SFTHs from the 2022 ACS. Ownership shares are calculated as authors' identified LTR holdings over total housing stock, SFTH units, and renter-occupied SFTH units, relying on a combination of official (ACS) and proprietary (CoreLogic) sources. Transaction shares rely solely on CoreLogic transaction data imputed from deeds records.

Table C2: Tract-Level Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Property Type Shares					
Single Family	0.622	0.264	0	1	84691
Townhome	0.059	0.098	0	1	84691
2-4 Unit	0.085	0.117	0	1	84691
5-49 Unit	0.122	0.153	0	1	84691
Other Homes	0.066	0.112	0	1	84691
Building Characteristic Shares					
No Bed	0.022	0.044	0	1	84691
1 Bed	0.108	0.113	0	1	84691
2 Bed	0.264	0.129	0	1	84691
3 Bed	0.401	0.152	0	1	84691
4+ Bed	0.205	0.152	0	1	84691
1 Room	0.02	0.041	0	1	84691
2-5 Room	0.482	0.193	0	1	84691
6+ Room	0.498	0.207	0	1	84691
1-10 Year Built	0.147	0.169	0	1	84691
11-20 Year Built	0.137	0.123	0	1	84691
21-40 Year Built	0.292	0.181	0	1	84691
40+ Year Built	0.424	0.288	0	1	84691
Market Conditions					
Log Rent	6.42	0.945	0	7.55	85160
Log Home Value	11.823	1.703	0	13.764	85160
Log Income	10.685	1.124	0	12.378	85160
Vacancy	0.122	0.106	0	1	84452
Socioeconomics & Demographics					
College	0.277	0.183	0	1	84609
Unemployment	0.099	0.061	0	1	84493
Poverty	0.161	0.129	0	1	84480
Non-Hispanic Black	0.137	0.215	0	1	84762
Asian	0.052	0.094	0	1	84762
Hispanic	0.162	0.227	0	1	84626
Landlord Share Changes (p.p.)					
Δ LTR Share	0.172	1.174	-58.657	62.88	78892
Δ 2-5 (SLL) Share	0.188	2.019	-100	100	78892
Δ 6-25 Share	0.011	2.669	-100	100	78892
Δ 26-150 Share	-0.097	3.039	-100	100	78892

Notes: This table summarizes the data used to estimate our LASSO regression and as controls in the endogenous OLS specifications. Data in levels from the 2010 Census. Landlord share changes span 2010-2022, in percentage points.

Table C3: First Stage Results, 2000's Boom and Bust Controls

	(1) Full Sample	(2) Δ LTR $\geq$ 0%	(3) Δ LTR in Top 10pct
		A. Prices	
Z-score Δ IV	0.086***	0.170***	0.214***
	(0.013)	(0.026)	(0.054)
Housing Supply Elasticity	-0.092***	-0.127**	-0.199
	(0.027)	(0.057)	(0.132)
Δ FHFA Price 00-06 (%)	-0.005***	-0.010***	-0.015***
	(0.001)	(0.003)	(0.005)
Δ FHFA Price 06-10 (%)	-0.018***	-0.038***	-0.052***
	(0.003)	(0.006)	(0.011)
Observations	416,102	142,729	38,660
First Stage F Stat	43.93	41.47	15.81
Δ LTR Mean (%)	0.0190	0.0580	0.164
Δ LTR S.D. (%)	0.127	0.199	0.337
		B. Rents	
Z-score Δ IV	0.101***	0.163***	0.122**
	(0.022)	(0.036)	(0.052)
Housing Supply Elasticity	0.011	0.060	0.097
	(0.052)	(0.083)	(0.129)
Δ FHFA Price 00-06 (%)	-0.005***	-0.007***	-0.008**
	(0.002)	(0.003)	(0.004)
Δ FHFA Price 06-10 (%)	-0.019***	-0.028***	-0.029***
	(0.004)	(0.005)	(0.006)
Observations	64,851	36,965	18,174
First Stage F Stat	21.14	20.39	5.574
Δ LTR Mean (%)	0.0640	0.113	0.209
Δ LTR S.D. (%)	0.231	0.290	0.381
		C. Homeownership	
Z-score Δ IV	0.092***	0.176***	0.213***
	(0.013)	(0.023)	(0.037)
Housing Supply Elasticity	-0.078***	-0.089	-0.077
	(0.027)	(0.060)	(0.118)
Δ FHFA Price 00-06 (%)	-0.005***	-0.008***	-0.010***
	(0.001)	(0.002)	(0.003)
Δ FHFA Price 06-10 (%)	-0.017***	-0.032***	-0.033***
	(0.003)	(0.004)	(0.005)
Observations	533,713	197,173	64,737
First Stage F Stat	51.66	57.82	33.71
Δ LTR Mean (%)	0.0260	0.0710	0.177
Δ LTR S.D. (%)	0.146	0.221	0.344

Notes: This table shows the first stage results for prices, rents, and homeownership. We control for house price dynamics over the prior boom (2000-2006) and bust (2006-2010) eras, as well as Tract-level supply elasticities from Baum-Snow and Han (2024). All specifications include county-by-year fixed effects. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

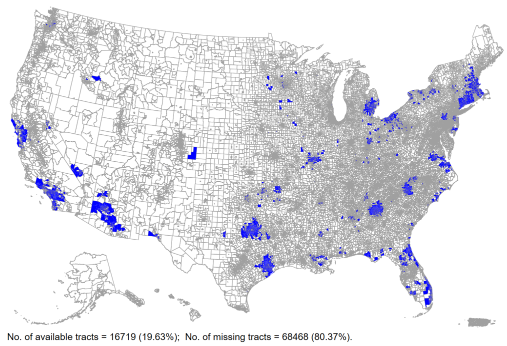
Table C4: Second Stage Results, 2000's Boom and Bust Controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Δ LTR ≥ 0%	Δ LTR in Top 10pct	Full Sample	Δ LTR ≥ 0%	Δ LTR in Top 10pct
	A. Prices					
	OLS			IV		
Z-score Δ LTR Share (Unit)	0.073***	0.055***	0.030**	2.087***	0.913***	0.849*
	(0.015)	(0.013)	(0.012)	(0.521)	(0.278)	(0.445)
Housing Supply Elasticity	-0.267***	-0.217**	-0.356***	-0.413***	-0.470***	-0.424**
	(0.050)	(0.092)	(0.082)	(0.091)	(0.130)	(0.187)
Δ FHFA Price 00-06 (%)	0.015***	0.014***	0.012***	0.029***	0.026***	0.030***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.008)
Δ FHFA Price 06-10 (%)	-0.029***	-0.035***	-0.032***	-0.011	-0.030**	-0.021
	(0.005)	(0.007)	(0.008)	(0.010)	(0.012)	(0.025)
Observations	416,102	142,729	38,660	416,102	142,729	38,660
R-squared or RMSE	0.714	0.761	0.782	4.222	3.945	4.284
Dep. Var Mean (%)	4.473	5.248	6.028	4.473	5.248	6.028
Dep. Var S.D. (%)	7.112	7.683	8.323	7.112	7.683	8.323
Elasticity (%)				16.43	7.189	6.685
	B. Rents					
	OLS			IV		
Z-score Δ LTR Share (Unit)	0.029	0.015	0.022	1.834**	0.436	-0.209
	(0.041)	(0.042)	(0.027)	(0.756)	(0.490)	(0.904)
Housing Supply Elasticity	-0.034	-0.125	-0.230	-0.162	-0.225*	-0.320
	(0.092)	(0.104)	(0.176)	(0.160)	(0.135)	(0.212)
Δ FHFA Price 00-06 (%)	0.006***	0.006***	0.001	0.019***	0.013***	0.003
	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)	(0.009)
Δ FHFA Price 06-10 (%)	0.008*	0.005	0.004	0.045**	0.017	-0.011
	(0.005)	(0.007)	(0.005)	(0.018)	(0.019)	(0.027)
Observations	64,851	36,965	18,174	64,851	36,965	18,174
R-squared or RMSE	0.221	0.294	0.383	7.714	6.579	5.555
Dep. Var Mean (%)	4.832	5.013	5.261	4.832	5.013	5.261
Dep. Var S.D. (%)	8.753	7.940	7.179	8.753	7.940	7.179
Elasticity (%)				7.939	1.887	-0.905
	C. Homeownership					
	OLS			IV		
Z-score Δ LTR Share (Unit)	-0.023***	-0.026***	-0.022**	-0.502***	-0.113	-0.030
	(0.007)	(0.008)	(0.009)	(0.122)	(0.086)	(0.124)
Housing Supply Elasticity	0.058***	-0.006	-0.033	0.101***	0.059*	0.017
	(0.021)	(0.033)	(0.060)	(0.028)	(0.035)	(0.056)
Δ FHFA Price 00-06 (%)	0.002***	0.002***	0.003**	-0.001	0.001	0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Δ FHFA Price 06-10 (%)	0.003***	0.004***	0.008***	-0.003	0.004	0.009*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.005)
Observations	533,713	197,173	64,737	533,713	197,173	64,737
R-squared or RMSE	0.046	0.059	0.077	3.277	3.374	3.558
Dep. Var Mean (%)	-0.150	-0.198	-0.278	-0.150	-0.198	-0.278
Dep. Var S.D. (%)	3.430	3.584	3.814	3.430	3.584	3.814
Elasticity (%)				-3.438	-0.774	-0.205

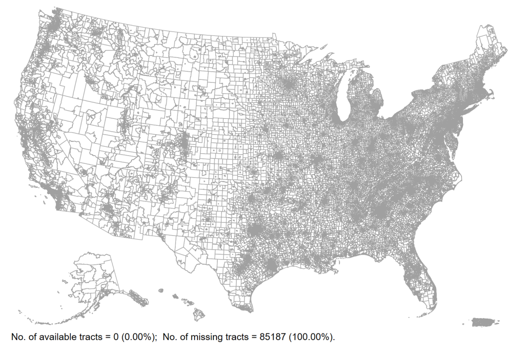
Notes: This table shows the first stage results for prices, rents, and homeownership. We control for house price dynamics over the preceding boom (2000-2006) and bust (2006-2010) eras, as well as Tract-level supply elasticities from Baum-Snow and Han (2024). All specifications include county-by-year fixed effects. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

D Appendix Figures

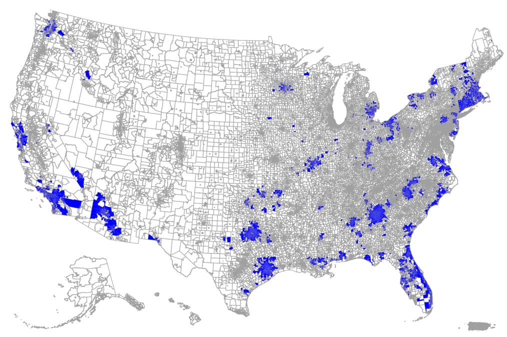
Figure D1: MLS vs. ZORI Coverage



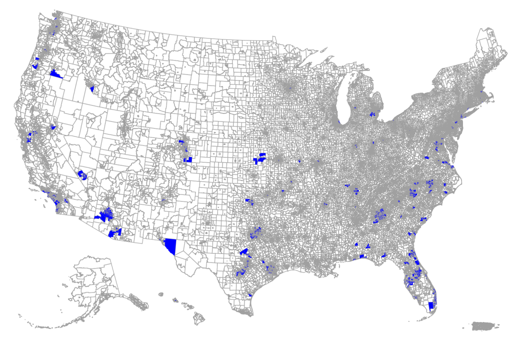
(A) MLS, 2010



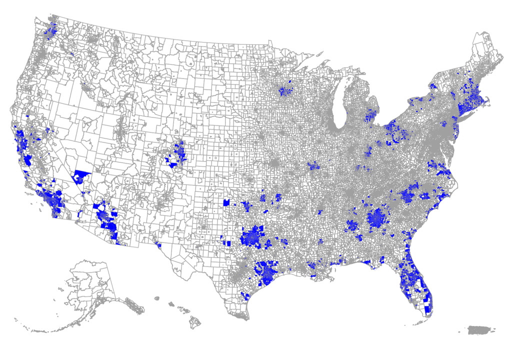
(B) ZORI, 2010



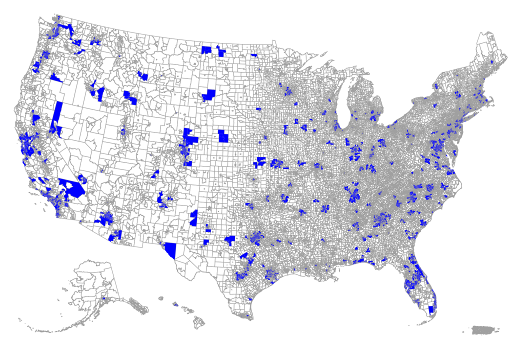
(C) MLS, 2016



(D) ZORI, 2016



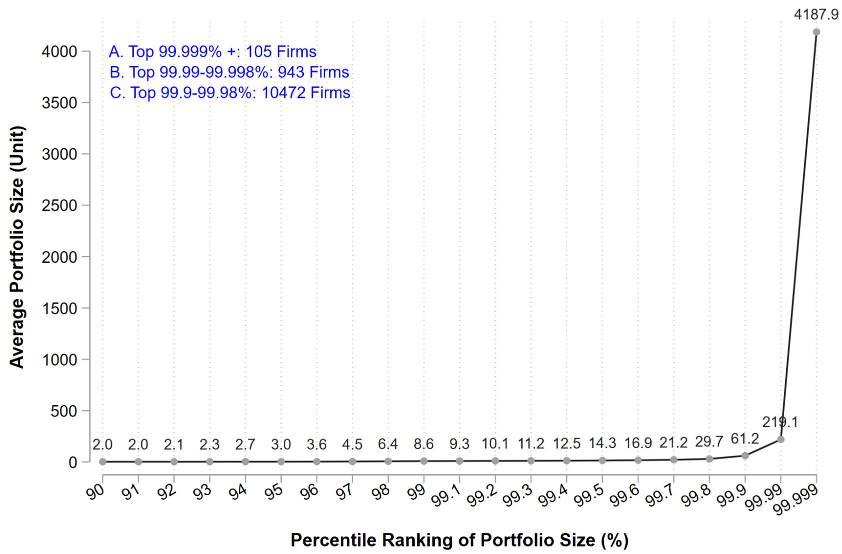
(E) MLS, 2022



(F) ZORI, 2022

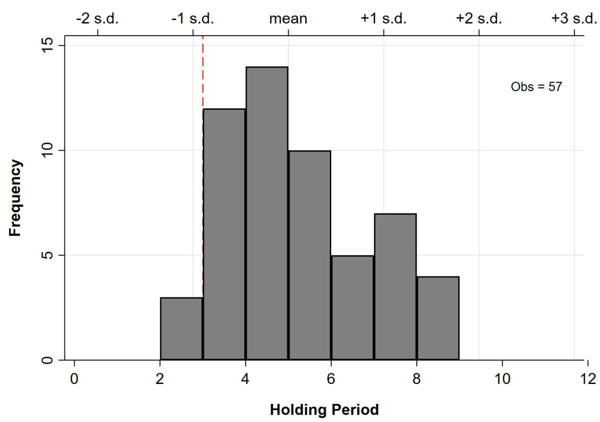
Notes: These maps plot the geographic distribution of CoreLogic MLS hedonic rent index and ZORI data availability, by year, across Census tracts. For sample construction see Section 2.

Figure D2: Distribution of Investor Size: Average Portfolio Holdings

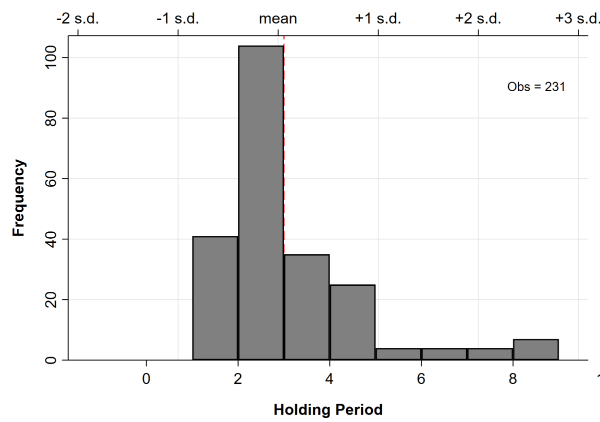


Notes: This figure plots the distribution of average portfolio size, by percentile rank in the holding size distribution. We limit to the top 10% of investors by holding size for ease of inspection.

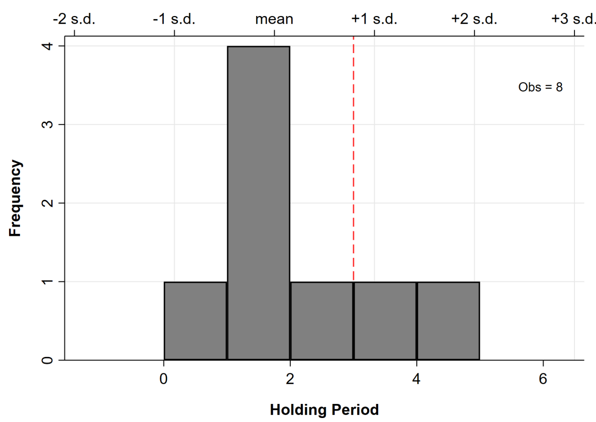
Figure D3: Distribution of Investors' Mean Holding Periods



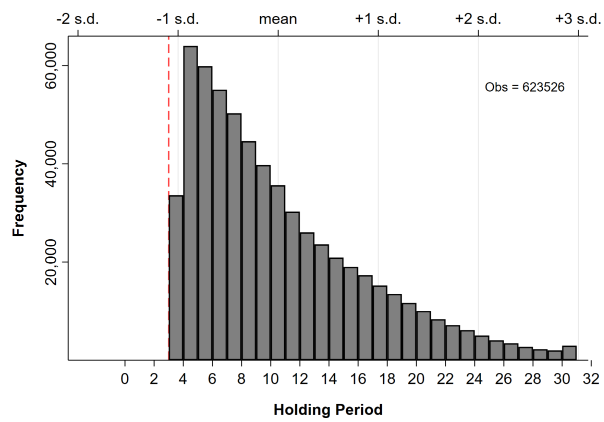
(A) LTR's



(B) Builders



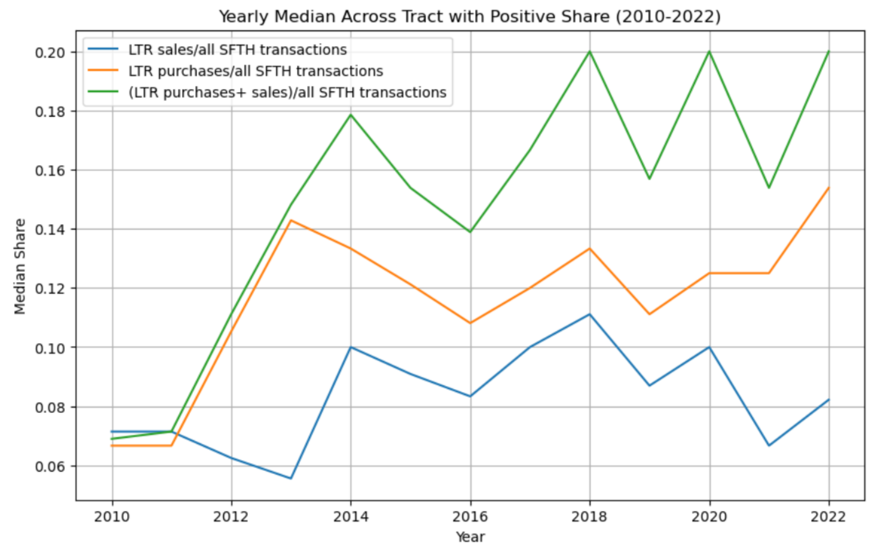
(C) iBuyers



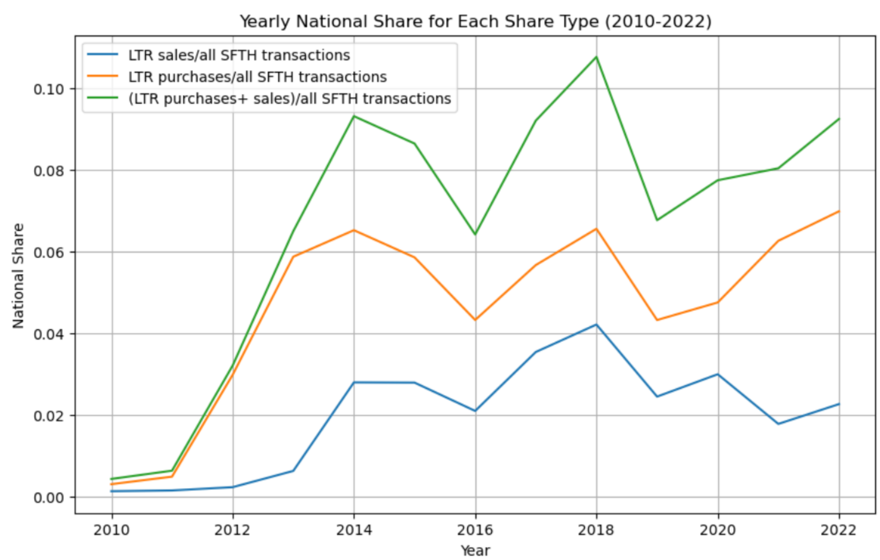
(D) Small Landlords

Notes: This figure plots the distribution of the average holding period for all properties within a given investors' portfolio between 2010 and 2019. Following DeFusco et al. (2022) and Bayer et al. (2020), we limit the sample of properties to those purchased by 2019, which allows for at least three years of post-purchase data. We also exclude iBuyers.

Figure D4: LTR's Share of Purchases, Sales, and Transactions 2010-2022



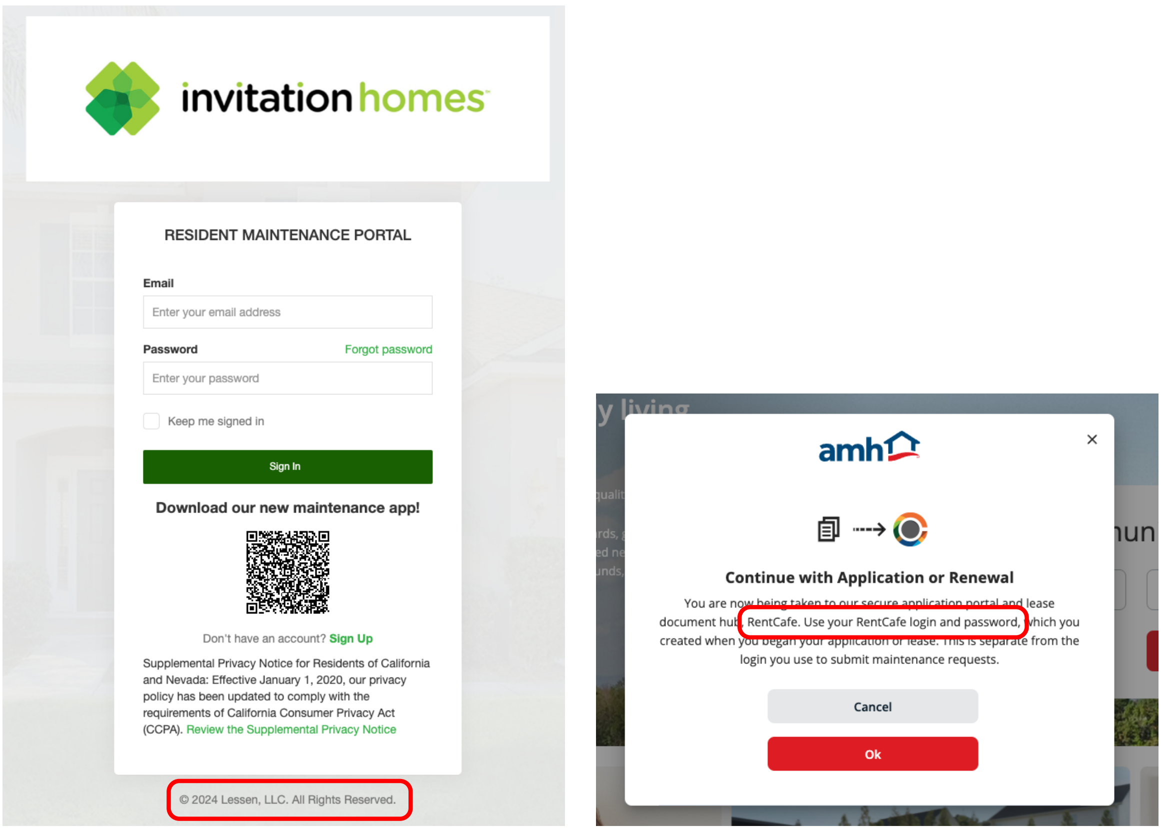
(A) Median Transaction Shares across Tracts



(B) National Transaction Shares

Notes: This figure plots LTRs' national transactions shares (panel (A)) and median shares across Census tracts (Panel (B)). Data was constructed using our annual ownership panel. Transactions are presented as purchases, sales, or (purchases+sales) relative to the total number of transactions. Sample limited to single-family and townhomes. Medians are conditional on positive market share.

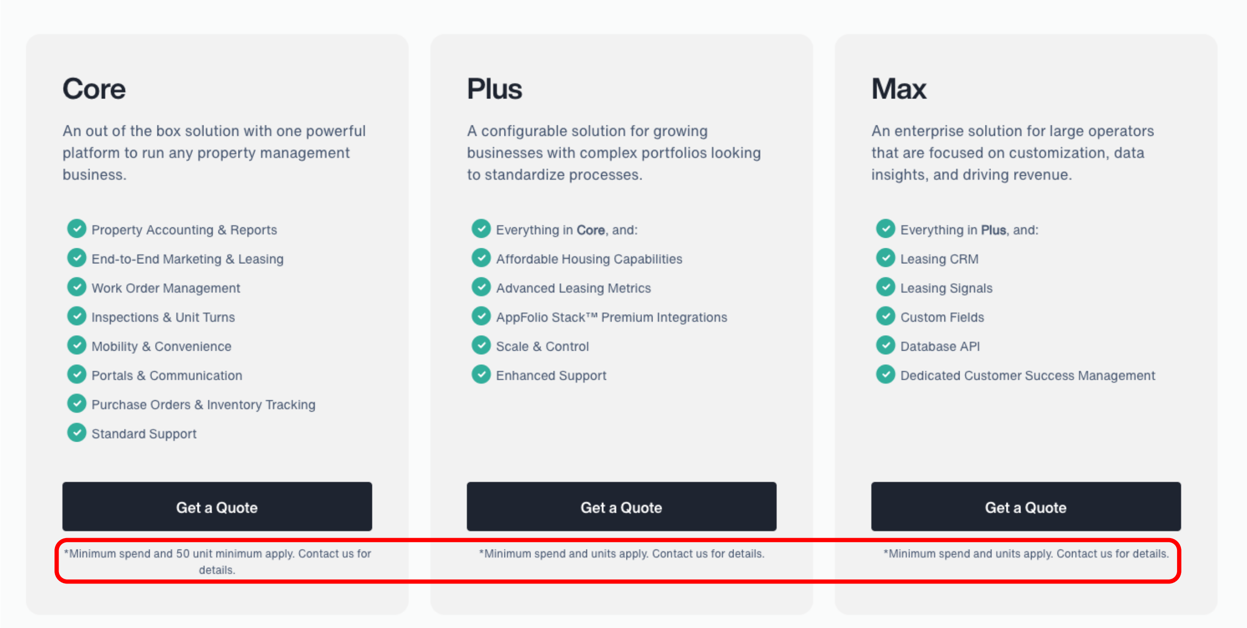
Figure D5: Public LTRs Use Third Party OPMs



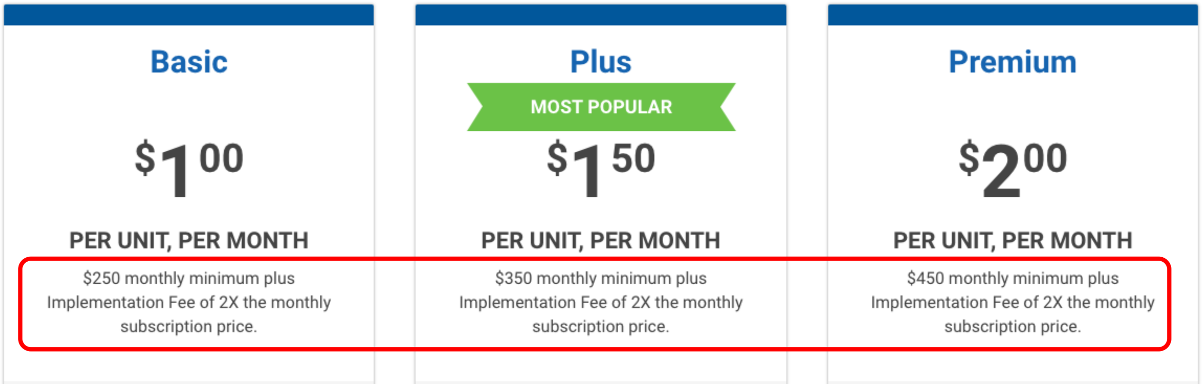
(A) Invitation Homes Maintenance Portal **(B)** American Homes 4 Rent Leasing Portal

Notes: Panel (A) shows where one is directed from https://www.invitationhomes.com/ after navigating to "Account Options" then "Request Maintenance" and finally clicking a button labeled "Request Service" at https://www.invitationhomes.com/maintenance-service-requests. Panel (B) shows the pop-up when navigating to "Log in" from amh.com, and choosing "application and renewal." Both screenshots were taken on October 9, 2024. Rounded red rectangles authors' addition.

Figure D6: More Examples of OPM Price Tiers



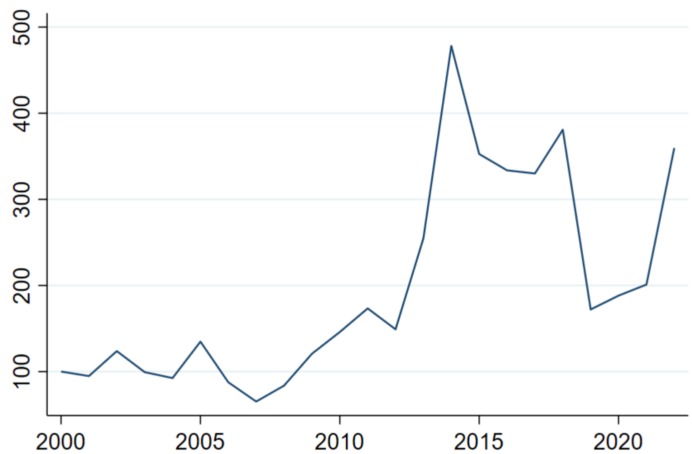
(A) AppFolio



(B) PropertyWare

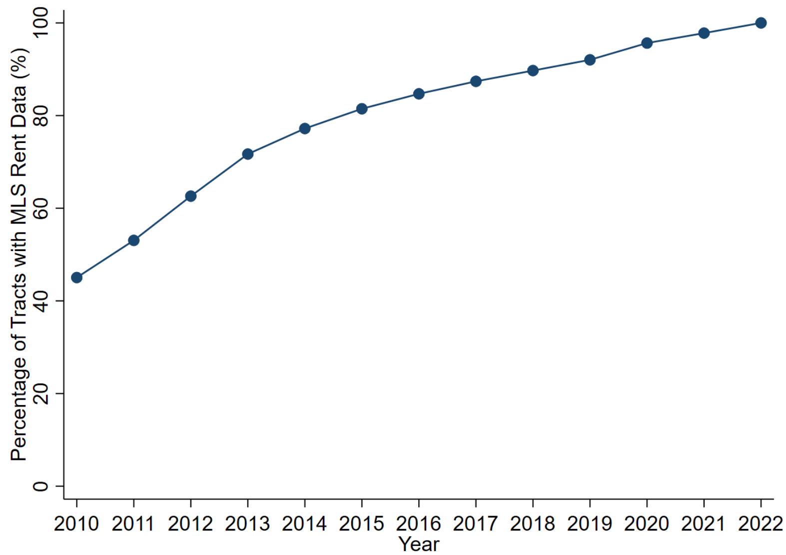
Notes: Panel (A) shows pricing for AppFolio, accessed on October 9, 2024. Panel (B) shows pricing information for PropertyWare on October 9, 2024. Rounded red rectangles authors' addition.

Figure D7: Index of Delaware Mailing Addresses among non-Delaware Homes

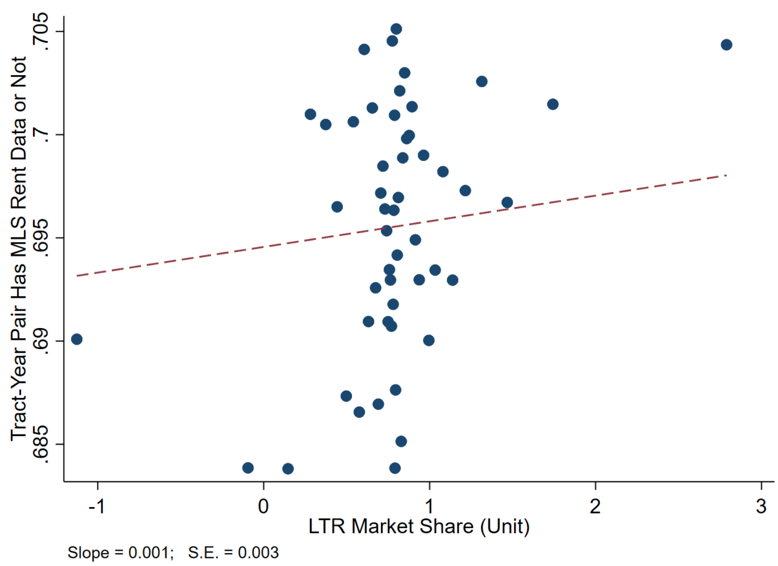


Notes: This figure plots the index of investor-owned, non-DE-located homes that have DE mailing addresses used for legal and tax purposes. The index is normalized to 100 in 2000. The increasing index likely reflects increased professionalization of landlords and utilization of professional registered agents, many of which (Corporation Services Company, Corporation Trust Company, etc.) have their offices in Delaware. Data from CoreLogic Deeds database 2010-2022.

Figure D8: CoreLogic MLS and LTR Entry Correlation



(A) Share of Tracts available over time in MLS



(B) MLS rent data availability vs. LTR market share

Notes: Panel A plots the cumulative entry of Tracts into our MLS listings data from 2010 to 2022. The plot illustrates the increasing share of Tracts covered in our data over time, reaching maximal Tract coverage in 2022. Panel B displays the relationship between the MLS rent data availability and LTRs' market share at the Tract-year level, pooling data from 2010 to 2022. The binned scatter plot controls for Tract fixed effects and county-year fixed effects with standard errors clustered at the county level.