Impact of Institutional Owners on Housing Markets*

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Abstract

Since the Great Recession, the rise of single-family rental companies has changed the investor ownership landscape in the U.S. Using housing transaction data, we document the rise of Long Term Rental (LTR) companies, defined as inclusive of single-family rental, rent-to-own, and real estate private equity firms, by constructing a panel of national single-family housing portfolios between 2010 and 2022. We show that LTR growth outstripped all other investor types, such as builders, iBuyers, and small investors, over the last decade. These companies geographically concentrate their holdings in select census tracts and expand their local market shares over time. To estimate LTRs' impacts on local housing markets, we construct a novel instrument predicting LTR entry, which we name the "suitability index." In the cross-section, this instrument leverages differential revealed preferences in product characteristics across landlord types. In the time-series, we interact these differential product preferences with a proxy for falling property management costs over time. In the first stage, more suitable locations for LTRs experience higher growth in LTR shares: a one-standard-deviation increase in the instrument implies a 23% higher annual growth in LTR share relative to the baseline mean. We use this instrument for LTR market entry to estimate the causal impact of LTR market share on local house prices. We find that a one-standard-deviation above the mean increase in LTR share growth leads to an annual additional house price growth of 2.11pp and additional rent growth of 2.19pp. Finally, we discuss how the reallocation of homeownership across small and large landlords, as well as owner-occupants and investors, contribute to these price increases.

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1 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. Since then, many other large investors have moved into the market, driven in part by the decline over the last decade's corporate and government bond yields, coupled with the rise in house prices and rents induced by historic under-building.

While often touted as a new type of villainous landlord, the economic implications of institutional ownership are ex-ante unclear. Investors can expand the single-family rental supply, either through partnering with builders to provide newly built-to-rent homes or by purchasing existing homes from owner-occupants and transitioning them to rentals. By expanding single-family rentals, investors offer new options to the subset of households unable to enter homeownership. Moreover, institutional landlords may not be as credit-constrained as individuals, leading to property renovations whose impacts on prices often spill over onto neighboring property values. While institutional investors may improve rental choice sets and housing quality, these benefits are attenuated if they displace residents who cannot afford to pay for improved quality or amenities. Institutional investors' impact on local house prices, rents, and resident composition thus becomes an empirical question we undertake to answer.

We use detailed housing transaction data to construct a novel data set of ownership spells. This yields the annual market value of real estate holdings for each owner-occupant, small landlord, or institutional investor. We find that investor holdings relative to owner-occupied holdings rose after the Great Recession, but that owner-occupants moved back into the market in the late 2010s, resulting in investor share stagnation. By the onset of the COVID-19 pandemic, investors lost ground to owner-occupants as demand for more spacious housing increased with the rise of telework.

If we break down the growth in investor ownership by size, we see that the largest firms tended to behave like the average investor: gaining market share after the Great Recession, before stagnating and losing ground to owner occupants during the COVID-19 pandemic. However, once we delineate investors by their main business model, we see that the largest institutional investors who specialize in providing long-term rentals, whom we refer to as LTRs, disproportionately grew between 2010 and 2022, comprising 0.02% of the investor market share in 2010, up to 0.36% of the investor market share by 2022. Given that the market share of *all* investors only grew from 12.1% of single-family units in 2010, to peak at 12.4% in 2015 (or among the top 0.01% of investors by size, from 0.7% of units to peaking at 0.9%), their growth alone explains most of the increase in investor portfolio holdings over this time. Indeed, other major institutional investors, such as builders or iBuyers, cannot explain the rise in investors' holdings, with builders losing market share, and iBuyers holding very little, due to their business as housing market liquidity providers.

We aggregate investor holdings for small landlords (SLLs) and long-term rental companies (LTRs) by Census Tract and year as a measure of each group's market penetration. We observe that the rise in investor share is highly targeted among neighborhoods with newer, mid-size, single-family units, in particular in neighborhoods 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, as discussed in Austin (2022).

While we wish to measure the impact of rising LTR shares on local house prices, these variables may also encourage entry such that we have a reverse causality problem hindering 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. To overcome these endogeneity concerns, we build a shift-share instrument leveraging cross-sectional variation in the pre-existing built environment and temporal variation in innovations in online platform management software.

Given the differential revealed preference for specific unit types between LTRs and SLLs, we exploit the pre-existing product mix in a location in 1990 to give us exogenous variation in the probability that investors enter a local market. To do so, we construct a "suitability index" based on how suitable 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. This yields the differential suitability particular to LTR entry relative to other landlords. Additionally, this index is orthogonalized to the endogenous socioeconomic and demographic characteristics, ensuring variation is driven by slow-moving product characteristics and not endogenous market characteristics, such as income levels or minority shares. The relevance condition requires that institutional investors differentially favor certain product types, while the exclusion restriction requires that these characteristics in 1990 would not impact changes in housing outcomes differently two decades later, except through their relative suitability to institutional investors. We present a placebo check to show that house price changes are balanced over the suitability index in the decade before the rise of LTRs, suggesting a lack of pre-trends in product characteristics driving differential price outcomes over our sample period.

We interact our cross-sectional variation in 1990 with a national measure of venture capital funds flowing into online property management (OPM) software startups; this provides a proxy for the declining cost of operating a disaggregated real estate portfolio. In constructing the temporal variation, we use a leave-one-out strategy wherein we remove the county-level number of firms in property management, scaling venture capital funding by the rest of the nation's property management establishment count. This ensures our temporal variation is not conflated with local changes in real estate markets attracting more landlords. Our identification strategy follows a two-stage least squares methodology in which we instrument institutional investors' market share with the interaction between falling operational costs and cross-sectional local suitability. We then regress local housing market outcomes on the instrumented market shares to analyze how the growth in institutional investors' market share impacts tract-level house prices and rents.

We estimate our two-stage least squares specification in changes-on-changes; the first stage specification regresses annual changes in a Census Tract's LTR share on changes in its instrument, while the second regresses annual changes in logged house price index or exact percent changes in rents on instrumented annual changes in LTR share. 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). We standardize both the changes in our instrument and our measure of changes in LTR market share. For the instrument, this is for ease of interpretation. For the annual changes in LTR market share, this accommodates the variable's marked skewness. For the second stage, we interpret the log difference in house price indices as percent changes and calculate exact percent changes in rents.

In the first stage, we find that a one standard deviation increase in the annual change in our instrument implies an increase of 0.034 in the standard deviation of LTR market share changes. This implies an increase in annual LTR growth of about 20% relative to a baseline mean. Our first stage F-statistic ranges from 16–44 depending on sample restriction, suggesting a strong first stage.

In the second stage, we find that a one standard deviation increase in instrumented LTR share growth causes a 3.84 percentage point (pp) increase in annual house price growth, and a minimal impact on rents. Focusing on Tracts with positive LTR market share by 2022, in which we leverage *intensive margin* variation in LTR shares, and exclude *extensive margin* variation (those Tracts with 0 LTR presence by 2022), the point estimate on prices drops to 1.64pp, which is statistically significant at the 1% level, while the impact on rents rises to 1.64pp, also significant at the 1% level. Interpreting the point estimate, a Tract experiencing a *1 standard deviation above the mean* change in LTR share would realize a 0.26pp increase in LTR share for our price sample, causing house price growth to rise by 2.11pp. For our rent sample, a 1 standard deviation above the mean LTR share change corresponds to a 0.4pp increase in LTR share within the shocked tract, which would induce 2.19pp additional rent growth.

We conclude by documenting two important sources of ownership reallocation that contribute to these price impacts not yet considered in the literature, in addition to the role of mergers and acquisitions facilitating increased LTR market share already studied (Gurun et al., 2022; Austin, 2022). First, the reallocation of stock from smaller landlords to larger, institutional landlords. Second, the reallocation of stock from owner-occupants to both small and institutional landlords.

The reallocation of rental stock among landlords is the most common form analyzed in the related literature; for example, Gurun et al. (2022) and Austin (2022) utilize three and four mergers, respectively, of two LTRs to provide exogenous variation in market concentration, a specific subset of landlord-to-landlord reallocation. We broaden this measure to study transitions from small landlords to other small landlords, small landlords to LTRs, and LTRs to other LTRs. Reallocation between small landlords should not have any new effects on prices or rents, while reallocation from small landlords to LTRs likely results in a growing portion of the rental market being exposed to algorithmic pricing, which has been shown to put upward pressure on rents through more dynamic repricing (Calder-Wang and Kim, 2023).

We also document the reallocation of stock between owner-occupants and investors, both small and large. In Tracts with larger LTR shares, we see that over the past decade, owner-occupants have been declining as a share of transactions. Indeed, owner-occupants and small investors have been selling to LTRs, who after they acquire homes, tend to trade amongst themselves rather than sell back to owner-occupants or small landlords. This has the effect of narrowing the owner-occupant stock, and thus pushing up the prices of single-family rentals in this cohort, while expanding the rental stock.

The overall price impacts point to rising prices under both sources of reallocation; more buyers are competing for limited stock, and the professionalization of the rental stock puts upward pressure on prices as rental net operating incomes rise. In contrast, the implications for rents are unclear; professionalization puts upward pressure on rents, while supply expansion puts downward pressure on rents. We intend to investigate these mechanisms further in ongoing work.

We contribute to three growing veins of literature on the role of investors in housing markets, their contributions to rising prices in their search for yield, and the impact these investors have on local affordability for residents.

The roles of varying types of investors in housing markets have garnered much attention since the Great Recession. Out-of-town buyers (Chinco and Mayer, 2016; Favilukis and van Nieuwerburgh, 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 are focused on the rise of institutional investors providing long-term rentals (LTRs), documented by Goodman et al. (2023) as having taken off since 2008. We contribute to this literature by highlighting the role of a new class of investors that arose after the Great Recession: the Single Family Rental companies and, more broadly, the role of private equity as landlords.

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.

Finally, 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 SFR companies' market concentration on local rents, in future work, we predict entry into a location based on 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.

Section 2 outlines our main data sets, how we construct investor portfolios, and how we classify investor types. Section 3 discusses the growth in the LTR industry, and their differential preferences for housing characteristics relative to traditional small landlords. Section 8 concludes.

2 Data

2.1 Main Datasets

Corelogic Deed Records and Tax Assessment: The core data set we use contains 200 million detailed deed records from the early 1980s to October 2022 for more than 2,400 counties[1] in the US. Our sample covers all single-family houses and townhomes, including information such as transaction dates, prices, addresses, buyer and seller information, etc. We only include non-arms-length transactions. We obtain property characteristics from the latest tax assessment updated by 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 discussed below.

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. We use data from the 1990 and 2000 Decennial Census as well as the five-year aggregates from the 2012 American Community Survey[2].

SEC 10K Fillings: We compile information on the subsidiaries for a list of publicly traded companies, such as REITs, single-family rental companies, or large asset managers in our data. Specifically, we find all subsidiaries for each parent company in each year during the horizon in which a company is active. This allows us to map the many small, legal subsidiaries used to purchase real estate to their parent companies when building portfolios of large, public institutional investors.

OpenCorporates: We also find many legal entities that purchase large amounts of single-family homes, but who are not obviously tied to a larger corporate entity. For example, American Homes for Rent does not purchase all of its properties using the legal name "American Homes for Rent." Instead, we find many examples in which large institutional holders of real estate portfolios have names such as "AMH4R Borrower YEAR-Q# LLC." For the largest 10,000 investors we identify after name harmonization, we search these legal entities using 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 in our data back to their parent company using OpenCorporates.com's lists of subsidiaries, and when that is not available, address matching among the legal entities and a list of corporate headquarters addresses.

Zillow Observed Rent Index (ZORI): This dataset provides our primary measure of market

[1] We only focus on the counties with more than 1,000 transaction records in total since the earliest date possible.

[2] 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.

rents. We use the smoothed and seasonally adjusted ZORI at the zip code level, and crosswalk the data to our sample of census tracts. In contrast to the data we use on house prices (either from the FHFA or our internally constructed HPI), the ZORI is only available from 2015 onwards[3]. The ZORI utilizes a repeat-rent methodology to estimate mean listed rent in dollars, sampling from the $40^{th} - 60^{th}$ percentiles of listed rentals, and using weights from the U.S. Census Bureau to reflect the composition of the underlying rental stock.

2.2 Constructing Ownership Panels

We use the CoreLogic Deeds database to impute the ownership and a fair market price for every single-family (detached or semi-attached) or townhome property in every year between 2000 and 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 have no more transactions for this home. We assign John Smith as the home's owner between 2004 and 2013, after which ownership passes to Jane Doe from 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 history varying over time between transactions. The property-year level ownership panel is our key novel data set for most analyses.

Hedonic Regressions: While we observe the price of a given home at sale, we do not observe all appraised values in between transactions since we are limited to tax appraisal data in 2022. In order to impute a fair market price for each property and year during 2000-2022, we run hedonic regressions at the county level and produce house price indices (HPIs) for each census tract and year in that county. Based on the actual transaction price(s) of a property[4], we then use the growth rate of HPIs to calculate fair market prices for all years during 2000-2022 for each property. A canonical example and several real cases are provided in Appendix A.1-A.3 to illustrate with details.

Below is the specification for the hedonic regressions:

$$\log(P_{i,j,t}) = \sum_{\tau \in [1,N]} \beta_{i,\tau} \mathrm{X}_{i,t,\tau} + \alpha_{j,t} + \phi_m + \varepsilon_{i,t}, \quad (1)$$

where $P_{i,j,t}$ is the price of unit i, in census tract j, in year t. $\mathrm{X}_{i,t,\tau}$ includes a suite of property characteristics including property age and its square, square footage, acreage, bedrooms, bathrooms, total rooms, and whether the unit has a garage or carport. $\alpha_{j,t}$ is a census tract-by-year

[3]Prior to May 2020, Zillow provided the *Zillow Rent Index* or ZRI, which tracked the median asking rent in a given location and month, and was available spanning 2011-2018. The ZRI was broken down into many other different sub-indices, for examples "All Homes" vs. "Single Family Rentals", no longer available at sub-metro geographies.

[4]Close to 60% transactions report transaction prices. We use the hedonic-predicted prices to fill in the rest of the missing transaction prices.

fixed effect, from which we construct our local HPI, and ϕ_m is a month indicator to control for seasonality in housing market cycles.

Figure 1: External Validity of Estimated House Price Index

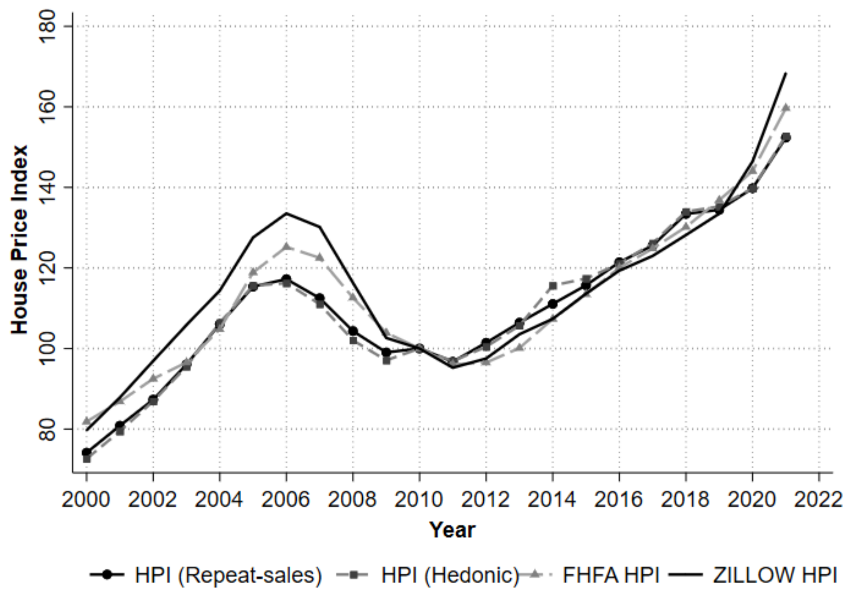


Figure 1 shows how our hedonic HPI performs against other commonly used house price index sources, namely from the Federal Housing Finance Agency (FHFA) and Zillow's Home Value Index. The FHFA uses a weighted repeat-sales methodology, which means it will miss price impacts of newly built homes that have not traded at least twice. Additionally, their sample is limited to detached single-family homes with conventional conforming mortgages; this means that the FHFA index misses the homes purchased using other loan types, such as jumbo loans or those securitized in the non-GSE market, as well as semi-detached homes and townhomes, which we include in our sample from CoreLogic. The Zillow ZHVI is a home *value* index, and uses data on all current homes' values, as imputed by their proprietary algorithm. This differs from standard methodology in that it uses both recently transacted homes, as well as homes that have not transacted to create their index.

We present both the hedonic and repeat-sales HPIs using our transaction data. When imputing values between sales, we prioritize using our hedonic prices, since this leads to wider geographic coverage; the data requirements for repeat-sales estimation can be quite taxing for fine geographies. Not only do we require many transactions in a small area, but the repeat-sales method requires observing houses trading twice. In any case, both of our measures track each other closely over the entire sample period.

Comparing our HPIs vs. the external sources, we see tightly correlated HPIs throughout the sample period, especially since the beginning of the recovery in 2010. Our series tracks the FHFA index quite closely between 2000 and 2005 as well, with gaps opening between 2006 and 2010, the most price-volatile period of the housing boom and bust. Compared to the Zillow ZHVI, all three other series fell below it between 2000 and 2010 before coming together.

Fair Market Price Imputation: As stated above, we use our HPIs to impute fair market prices for a gap or missing years when a property was not transacted. We also use hedonic-predicted prices to fill suspicious prices that lay far outside the local house price distribution, for example, those with abnormally high prices, or transactions that seem to be purchased together on the same date, and which share an incredibly high price suggesting the price reflects the value of the entire bundle rather than the individual unit. We identify "chunky" transactions as those transactions that happened on the same day, at the same abnormally high price[5], with the same buyer. These chunky transactions are typically associated with institutional buyers such as builders and rental companies that buy tens or hundreds of properties all at once. Appendix A.4 provides several examples of these chunky transactions.

2.3 Building Real Estate Portfolios

One of our goals is to be able to identify different types of investors in our sample, specifically by their portfolio size. We aggregate the property-year ownership panels over investor names to build real estate portfolios for each investor each year. We limit this sample to institutional investors of our interest, excluding legal entities that use common individual names so that we don't over-aggregate small investors (i.e. "John Smith, LLC"), family trusts, as well as public, non-profit, and government entities. We 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, we have to include some individual or family trusts in 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[6].

Name Harmonization: Based on the aforementioned investor list, we would like to uniquely identify each investor over time even though an investor has different names reported in the data. Due to the complexity of buyer and seller names, we use the RapidFuzz Python package, which calculates the Levenshtein string distance and fuzzily matches strings, to harmonize similar investor

[5] Higher than the 95th percentile of all historical transaction prices within a county.

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

names and collapse them to represent one unique investor entity. 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: On top of algorithmic name harmonization, we also hand-collect all subsidiary names reported for each publicly traded investor in each year from 10K filling. This step is crucial to identifying all entities of an investor because many subsidiary names do not resemble the name of its parent company. We collect a list of publicly traded firms from industry reports and scrape the SEC 10k filings for their lists of subsidiaries. We collapse all property holdings of these subsidiaries into their parent company. Detailed descriptions and examples can be found in Appendix A.5.

Private Subsidiaries: For the firms that are active investors in our data but 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 we start constructing our investor-level portfolios is to differentiate potentially small investors from the large investors of our interest. For example, there are a large number of housing units owned by the same harmonized name "Rodriguez, Jose" although this name corresponds to thousands of different investors such as "Rodriguez Jose Trust", "Rodriguez Jose Fam Trust", "Rodriguez Jose LLC", etc. We manually flag thousands of small investors like this and 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 Orange County. We manually identify among our top 10,000 investors whether they appear to be aggregations of many smaller, individual landlords, as in the example above, or a larger institutional 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, their total estimated market value, and investors' annual transaction volumes in value and units, as well as broken down by sales and purchases. This data set allows us to track the number and the market value of the 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 homebuilding companies such as D.R. Horton, Lennar, NVR, and the Pulte Group. These builders regularly top industry reports of the largest builders, measured either by revenue or production. Additionally, we have been able to identify six large LTRs: Invitation Homes, American Homes 4 Rent, Progress Residential, FirstKey Homes, Tricon Residential, and Home Partners of America.

Table 1: Categorization of the Top 20 Institutions

Rank	Name	Category	First Active	Last Active	Avg. Holdings (units)
1	D.R. Horton	Builder	1978	2023	46422
2	Lennar	Builder	1954	2023	28932
3	Pulte Group	Builder	1950	2023	27869
4	**Invitation Homes**	SFR	2012	2023	25678
5	**American Homes 4 Rent**	SFR	2012	2023	24388
6	NVR	Builder	1980	2023	12477
7	**Progress Residential**	SFR	2012	2023	10100
8	**FirstKey Homes**	SFR	2015	2023	7638
9	KB Home	Builder	1957	2023	7559
10	U.S. Bank	Holding	1863	2023	6683
11	Tri Pointe Homes	Builder	2009	2023	6501
12	DSLD Homes	Builder	2008	2023	6310
13	Meritage Homes	Builder	1985	2023	6040
14	Clayton Homes	Builder	1956	2023	5747
15	**Tricon Residential**	SFR	1988	2023	5210
16	Highland Homes	Builder	1985	2023	4884
17	M.D.C. Holdings	Builder	1972	2023	4214
18	LGI Homes	Builder	2003	2023	4060
19	Century Communities	Builder	2002	2023	4040
20	**Home Partners of America**	SFR	2012	2021	3903

Notes: Authors' calculations of mean portfolio holding size (in units) of single-family homes for the top 20 largest firms in our sample. Portfolio holdings averaged between 2000-2022; for companies established post-2000, the average is restricted to *active* years so as not to attenuate calculations towards zero.

The first five 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.[7]

These six 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, with the latter two incorporated at Real Estate Investment Trusts (REITs). 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,[8] and Blackstone purchased the rent-to-own business Home Partners of America in 2021, and formerly owned Invitation Homes before it went public.

Among all 43 LTRs we identify in our sample, they collectively own 328,510 units by 2022. However, we likely undercount many portfolios as we cannot map individual deeds to parent companies perfectly 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 most of our market-level analysis, instead aggregating holdings across firm *types* described in the next subsection, these portfolios are key inputs into our investor categorizations; in particular affording us a measure of portfolio size in either units or value.

2.4 Categorizing Firms

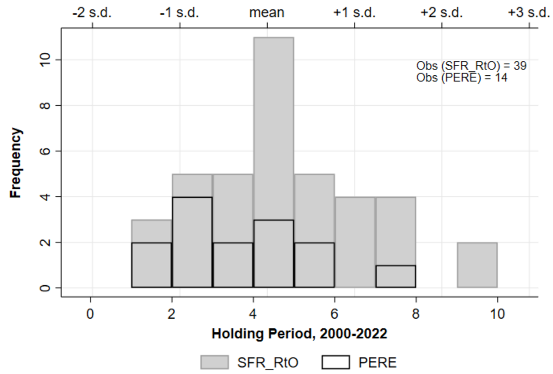
Using the aggregated portfolio holdings, we can categorize firms by type, or purpose, as well as by size.

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 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 C3 Panel (A) shows the mean holding period distributions for private equity real estate firms (PERE), as well as single-

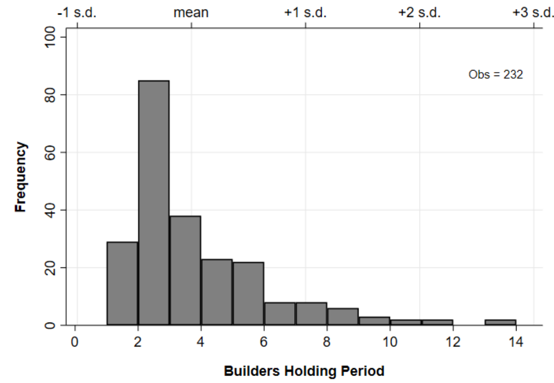
[7]For a discussion of Home Partners of America's lending and leasing activity, see "Private equity sold them a dream of home ownership. They got evicted instead." by Rebecca Burns, of *Business Insider*, July 7, 2023. Accessed at https://www.insider.com/home-partners-rent-to-own-low-success-rate-2023-5.

[8]Pretium Partners also acquired Front Yard Residential, which is another LTR in 2021.

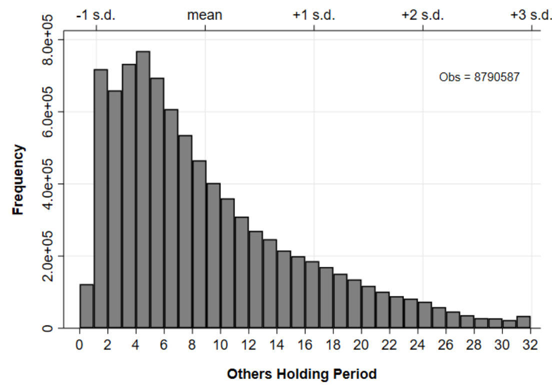
Figure 2: Distribution of Investors' Mean Holding Periods



(A) SFR's and PERE's



(B) Builders



(C) Other

Notes: This figure plots the distribution of the average holding period for all properties within a given investors' portfolio between 2010 and 2019. Following Bayer et al. (2020) and DeFusco et al. (2022), 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 since they, by definition, are not actively renting out properties.

family rental companies and rent-to-own companies (SFR_RtO). 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 purchase and eventual sale. 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. Additionally, 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 the investors that 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 for the descriptive institutional background of the non-owner-occupied housing market.

Builders: These firms primarily build new housing, though, in the later years of our sample, many will have 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, with their holding period distribution skewed left, as shown in Figure C3 Panel (B). Since many of these large builders build entire communities, not just individual units, most end up holding units for fewer than 5 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 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.

Other: We do not use this group in our main analysis. This group includes investors who own only one property, smaller speculators (i.e. not iBuyers, may hold more than 1 unit but on average for $\leq$ 3 years), government and public entities, universities, non-profits, and other institutions we think are not operating in the competitive rental market.

Breaking down the top 1,127 largest firms ranked by average portfolio holding size in units (top 0.01%), we can look at the investor type composition. These firms consist of 36 LTRs, 203 builders, 6 iBuyers, and 882 non-categorized investors. Of the LTRs, 27 firms list their main business model as being providing single-family rentals, single-family build-to-rent, or single-family rent-to-own. Another 9 LTRs are private equity real estate (PERE) companies. Zooming out to the top 1% of firms, we are able to categorize 41 total LTR companies, 232 builders, and 9 iBuyers among the largest 0.1% of 112k investors.

As a check that our portfolio construction matches reality, we collect reported holdings from the 24 LTRs that remain active in our sample as of the end of 2022. 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 to our estimates understating the total portfolio holdings in the case of recent mergers and acquisitions, such as Invitation Homes' purchase of nearly 2,300 homes in September 2023.[9] Figure 3 shows our estimated holdings in gray, overlaid with firms' 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.[10] 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 are able to capture the broader trends in LTR shares over time and across Census Tracts.[11]

3 Growth in Institutional Investors' LTR Portfolios

In this section, we describe the evolution of the LTR portfolios and their market penetration.

3.1 National Level

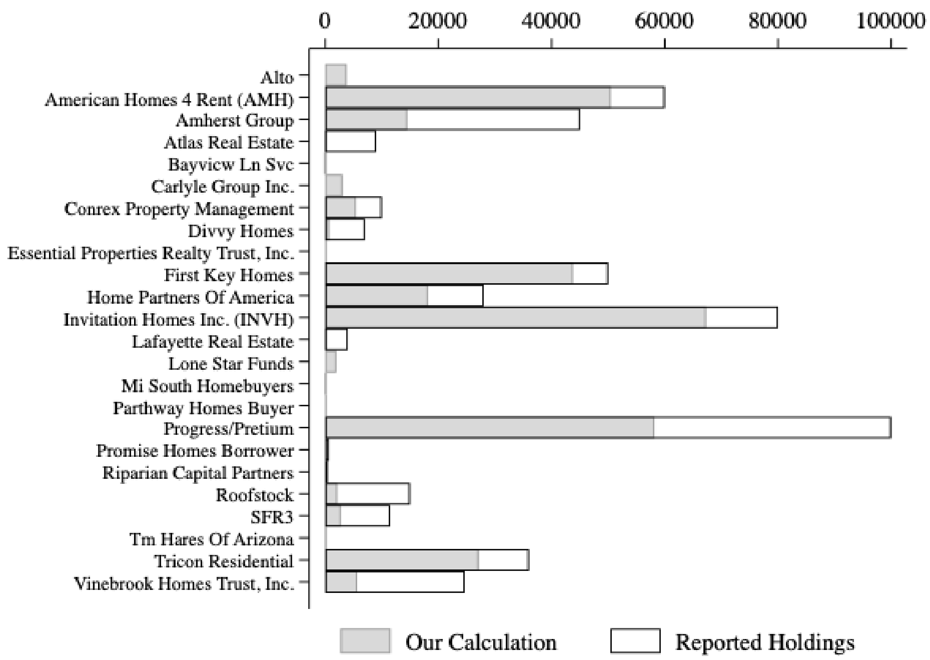
Having constructed time-varying portfolios for individual investors, we first analyze investors' market share relative to owner-occupants. Figure 4 panel (A) plots the market share of all investors between 2010 and 2022, by their portfolio holdings in units. We see that coming out of the Great Recession, investors acquired large numbers of single-family units, increasing their market share from 12% in 2010 to 12.4% at their peak in 2015. Their market share plateaued between 2015 and 2020, before falling sharply during the COVID-19 pandemic, as demand for home ownership, especially in less-dense single-family homes soared among owner-occupants. Panel (B) plots the same holding share in units but zooms in on the largest investors in our sample. The top 99.9% of firms, as ranked by their mean portfolio size, represent 11,270 unique firms. These firms owned

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

[10]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.

[11]As of 2021, FirstKey Homes was taken private by Pretium Partners, which already wholly owned Progress Residential. As of now, the two LTRs, FirstKey and Progress 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.

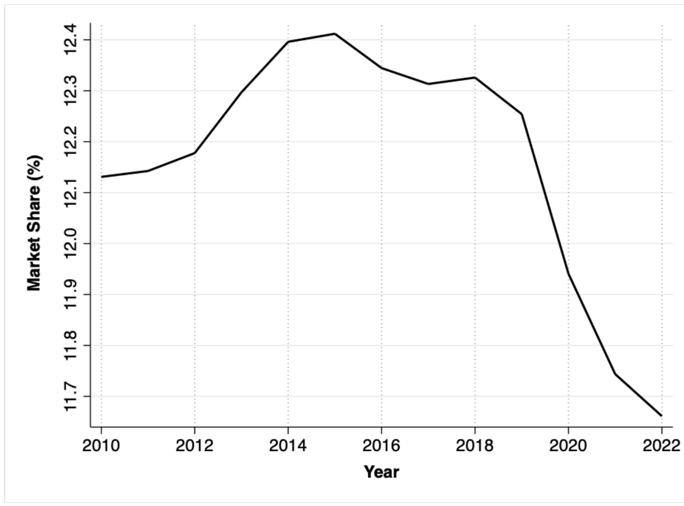
Figure 3: LTRs' Estimated (2022) vs. Reported Holdings (2023)



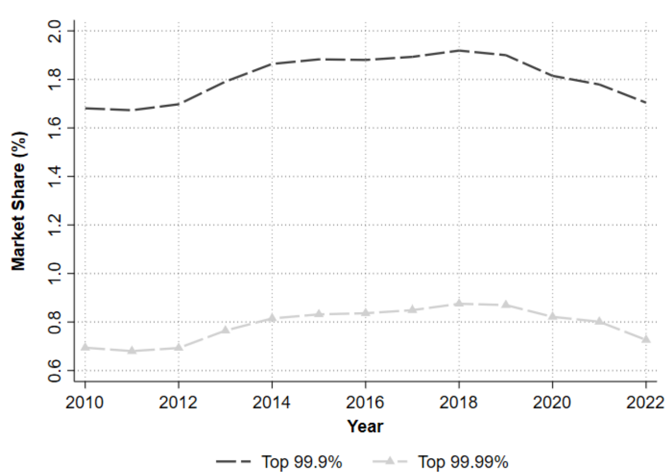
Notes: This figure compares our estimated single-family and townhome holdings as of December 2022 to reported holdings on firms' websites as of December 2023. We limit the sample of LTRs to those still active in 2022, defined as having positive single-family or townhome holdings; this removes previously active LTRs that were acquired by other entities, or which discontinued their single-family rental business.

about 1.7% of all single-family housing units in 2010, building up their market share to 1.9% by their 2019 peak. Falling market share after 2020 again reflects the rise in homeownership during the pandemic, with homeownership rates rising from 64% in 2019q1 to 65.9% in 2022q2. The largest investors, indexed by the top 99.99% line, reflect the 1,127 firms we discussed at the end of Section 2. These investors saw similar national trends, rising from 0.7% of the single-family housing stock in 2010 up to 0.9% of the stock in 2019, before losing market share to owner-occupants.

Figure 4: Investors' National Share of Single-Family Housing Stock Over Time



(A) All Investors



(B) Top 0.1% of Investors by Holding Size

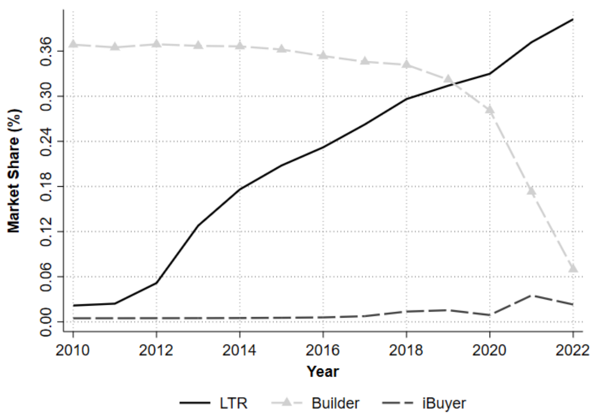
Notes: These figures plot the national market share of properties owned by investors, rather than owner-occupants. Panel (A) shows the market share among all investors, while panel (B) shows the share among the largest investors, as measured by the average portfolio holding size in units between 2010 and 2022.

We can break down the growth in investor share by firm type, as outlined in Section 2.4. In figure 5, we plot single-family portfolio holdings in housing units, differentiating investors by their main business model: LTRs, Builders, and iBuyers (we remove "others" and SLLs from the figure for ease of inspection). In Panel (A), we plot the market shares by investor type among all *investors*, the denominator is now total investor holdings of single-family units rather than all single-family units, owner-occupied or investor-owned as in Figure 4. We see that among investors, the 53 LTRs in our sample grew from a negligible market share in 2010, before this sector began with Blackstone's acquisition of thousands of homes purchased out of foreclosure auctions, to nearly 0.4% by 2022. By 2022, these 53 firms owned 328,510 units. iBuyers 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, as their business model is to buy and quickly sell homes, keeping portfolios small. We show in Appendix Figure C1 that iBuyer's *transaction* share grows quickly between 2018 and 2022, confirming that we are able to capture their behaviors consistent with their stated business model. Finally, homebuilders make up the largest market share segment among our largest categorized investors for most of the sample. They consistently represented about 0.36% of investor holdings until 2018, when their market share began to decline. During the COVID-19 pandemic, their holdings fell quickly as new households moved into homeownership at fast rates, and we see in Appendix Figure C1 that their *transaction* share shoots up in 2020 and 2021.

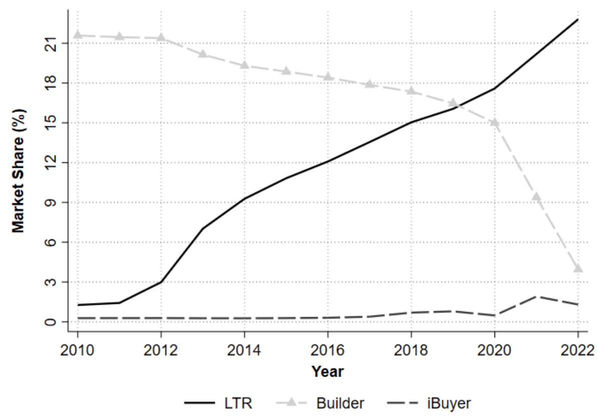
Focusing again on the largest investors in our sample, we can restrict the denominator to be all single-family unit holdings among the top 0.1% largest investors, or the top 0.01% largest investors. Figure 5 Panels (B) and (C) show a similar story as in (A), but the growth in LTRs is more striking. LTRs grew from minimal holdings in 2010, and make up 22%–56% of the holdings among the largest investors in our sample, while builders lose market share and iBuyers mechanically gain very little. In sum, Figure 5 shows that the rise in investor market share we saw in Figure 4 can be entirely attributed to the new single-family long-term rental industry, with the attenuation in market share after 2019 coming from builders' stock of available homes falling as homeownership rose during the COVID-19 pandemic.

Not only have these LTRs grown to represent a sizeable share of the total stock of single-family rental units, holding 328,510 units by 2022, but these holdings are in increasingly concentrated locations. Figure 6 shows how holdings have concentrated in space over time. In Panel (A), we plot the distribution of LTR's *Census Tract-level* market shares over time. In 2010, the 95^{th} percentile tract of LTR concentration was 0.62%, and the median tract had an LTR market share of 0.11%, which is very similar. By 2022, these tracts have diverged significantly, with the median tract having roughly the same share of single-family units owned by LTRs as it did in 2010. In contrast, the 95^{th} percentile LTR market share tract saw about 4.3% of its single-family homes owned by LTR investors. Figure 6 Panel (B) shows a similar story: while all Tracts saw increasing LTR presence between 2010 and 2022, the right tail is growing at a faster rate. Comparing the 99^{th} percentile tract in 2010 vs. 2022, LTR market share grew from 2% to upwards of 8% such that in the most concentrated tracts, 1 in 12 homes is now owned by LTR investors.

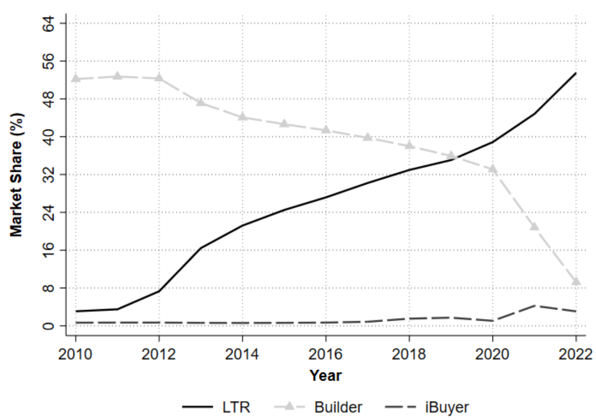
Figure 5: Investors' National Market Shares of Single-Family Portfolio Holdings, by Type



(A) All Investors



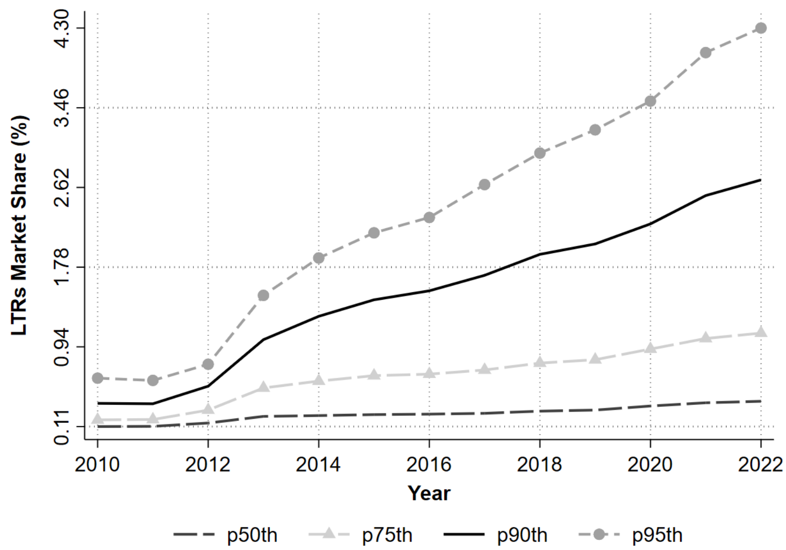
(B) Top 0.1% of Investors by Holding Size



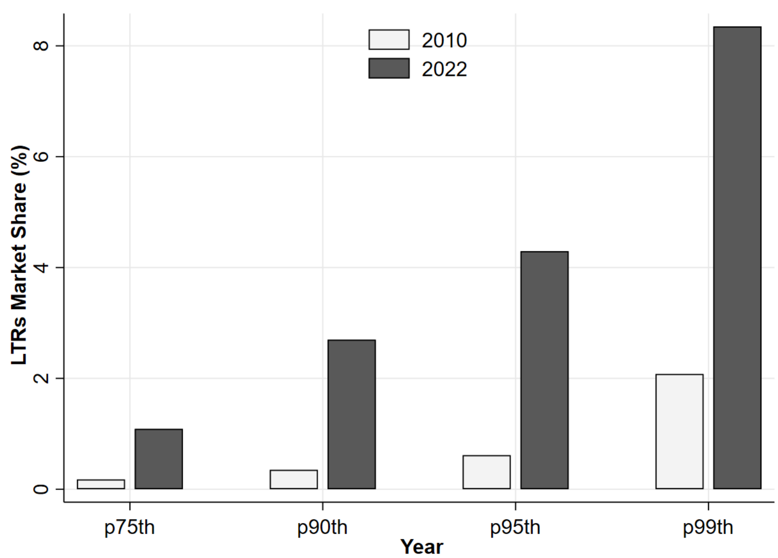
(C) Top 0.01% of Investors by Holding Size

Notes: These figures plot the national market share of firms identified as LTRs, Builders, and iBuyers between 2010 and 2022, as measured by their portfolio holdings of single-family homes. Data from CoreLogic Deeds aggregated to firm-year level. Investors ranked by size based on percentile in the distribution of average portfolio size in units of single-family houses.

Figure 6: Distribution of Investor Holdings has Become More Concentrated



(A) Tracts over Time



(B) Tracts by Percentile

Notes: These figures plot the distribution of local LTR market shares between 2010 and 2022, as measured by their portfolio holdings of single-family homes. Data from CoreLogic Deeds aggregated to LTR-tract-year level. Panel (A) plots the widening gap between the 50^{th} and 95^{th} percentile tracts by LTR market share over time. Panel (B) plots the change in LTR market share for four percentiles between 2010 and 2022.

3.2 Targeted Properties and Demographics

The media have described the rise of LTRs over the past decade 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 Census 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 Census 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.

Table 2 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 2 also shows how different categories of landlords evolved between 2010 and 2022. At first glance, it may seem that LTRs saw minimal market share changes, with the average Tract realizing only a 0.17 percentage point increase in LTR share, 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 6 shows that these LTRs tend to concentrate their holdings in space. Moving along the columns in Table 2, we see that the maximal Census Tract saw LTRs' market share grow by 63 percentage points. Other small landlords also grew in the average Tract, by 0.19% for all landlords holding 2-5 units, and 0.01% for all landlords holding 6-25 units. The largest non-institutional landlords, those with 26-150 units seem to have contracted, on average losing 0.1 percentage points in market share as a group. Taken together, LTRs and the smallest landlords seem to be growing in presence at the expense of medium and

Table 2: Summary Statistics of Market Shares, Product, Demographic, and Socioeconomic Characteristics

Variable	Mean	Std. Dev.	Min.	Max.	N
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
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
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
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
Δ LTR Share (%)	0.172	1.174	-58.657	62.88	78892
Δ 2-5 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 shows the summary statistics for univariate housing product characteristics and neighborhood-level socioeconomic and demographic controls. The sample reflects 2010 characteristics among U.S. census tracts.

larger non-institutional landlords.

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 composition to predict changes in market shares for different 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 change in market share (measured by the market value of 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 β_j reveal the landlords' preferences for different product mixes, presented in Table 3 Panel (A). Column (1) of Table 3 presents the LTRs revealed preferences, column (2) the revealed preferences of landlords who own 2-5 units, and column (3) shows their 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.

Table 3: 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.

Panel (B) of Table 3 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.

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.

4 Impact of Institutional Investors on Local Housing Markets

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:

$$Y_{it} = \alpha + \beta \Delta \text{LTRshare}_{it} + \varepsilon_{it}. \tag{3}$$

Here, Y_{it} is the outcome of interest for Census Tract i in year t. For example, it could be the levels of or changes in house prices or rents at the Tract level. $\Delta\text{LTRshare}_{it}$ is the change in the share of single-family homes in Tract i owned by large LTRs in year t.[12] 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 identification concern is simultaneity: unobserved location characteristics could be driving both housing market dynamics and attraction of LTRs. For example, large LTRs are attracted to enter places with rising rental demand for single-family homes brought by job entries that pay high wages. 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 point estimate downwards. Last but not least, we could underestimate LTRshare_{it} due to measurement error, leading to attenuation bias in β. 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.

[12] 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.

4.1 Research Design and Identification

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.[13]

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.

4.2 Cross-Sectional "Share" Variation: LTR–Specific 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 3. 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:

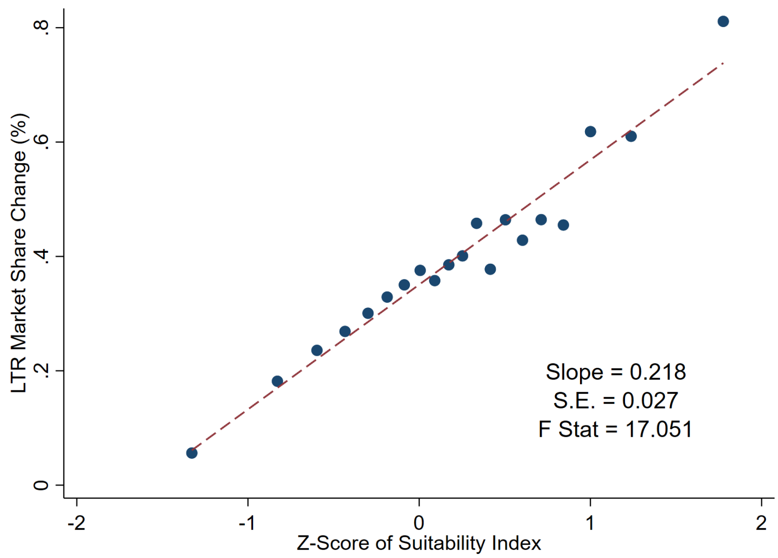
$$S_i = \sum_j \hat{\beta}_j \times \text{Prop}_i^{1990,j}. \tag{4}$$

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, 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

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

that are orthogonal to any influence of socioeconomic and demographic variables since we do not include their coefficients from Panel B of Table 3. The cross-sectional differences in neighborhoods' suitability indices serve as local "pulling factors" to attract LTRs to enter as landlords.

Figure 7: Partial First Stage



Notes: This figure shows a binned scatterplot as well as a linear fit 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, local house price elasticities of supply borrowed from Baum-Snow and Han (2023), and control for house price dynamics over the boom and bust periods before 2010.

The binned scatterplot in Figure 7 displays the relationship between the Z-score of our suitability index, S_i, and the change in LTR share in a given Census Tract between 2010 and 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 least in the cross-section, 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 their later entry. Interpreting the slope, we see that a 1-standard deviation (0.52) increase in the Suitability Index predicts a 0.22 percentage points greater actual increase in LTR market share during our sample period. The F-statistic is around 17.1. Additionally, the graph shows evidence of convexity, especially in the positive Suitability Index range, consistent with LTRs concentrating their holdings in particularly well-matched locations, as in Figure 6.

4.3 Temporal "Shift" Variation: Declining Costs of Decentralized Management

Next, we build the "shift" component of our instrument. In talking with industry professionals, many brought up the rise in 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.[14] This high multifamily share reflects the historical challenge of providing services to geographically dispersed properties relative to having a management office or superintendent in a multifamily building.[15] 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 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 8 plots the cumulative amount and rounds of funding received from venture capitalists (VC) by OPM companies. 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.[16] 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 factor" attracting new landlords to enter the rental market, as increased competition offers cheaper property management solutions and different options. This is true particularly for LTRs and larger landlords as many of these OPMs have a minimum unit requirement.[17]

4.4 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-

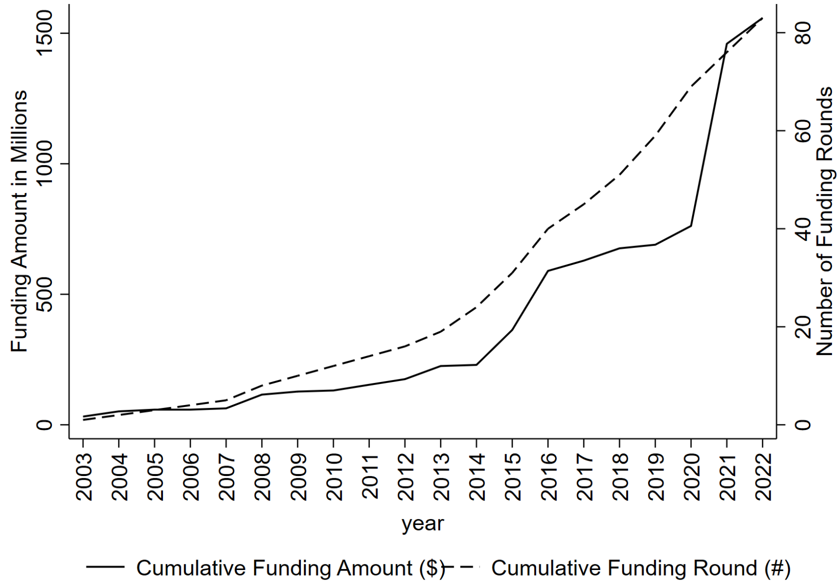
[14] Author's calculations using 2022 national Census data, excluding rental units in mobile homes, boats, or RV's.

[15] 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

[16] 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.

[17] For example, AppFolio, one of the largest national OPM platforms, requires a landlord to have a minimum of 50 units 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. https://www.appfolio.com/property-manager accessed on 2/10/2023.

Figure 8: 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.

family properties, shifts in the potential market size for OPM, and local product suitability together act as "push" and "pull" factors encouraging firms to venture into the LTR business in a local housing market.

To operationalize 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 unique "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 helps remove any correlated idiosyncratic shocks within a region that may arise from the industry-location dynamics of PM expansion, potentially introducing endogeneity. To create our instrument that is predictive of the annual change in the shares of single-family homes owned by LTRs in a Census Tract, 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 and interpretation. Formally, our instrument, IV_{it}, is defined as:

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

4.5 Two-Stage Least Squares Design

Estimation Equations

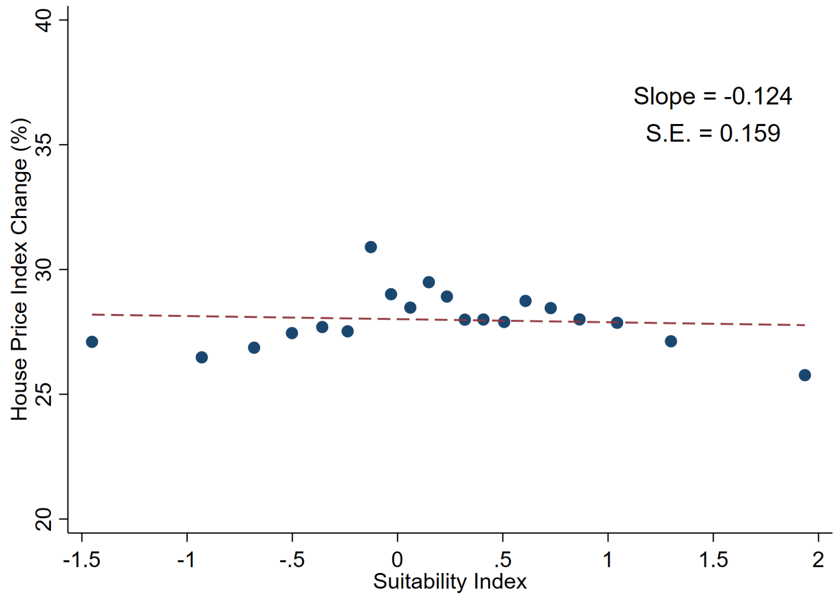
We estimate the relationship between the rising LTR shares and local housing market outcomes using the following empirical framework:

$$\begin{aligned}
&OLS: && Y_{it} = \beta \Delta \text{LTRshare}_{it} + \boldsymbol{X}'_{it}\Gamma + \varepsilon_{it}, && (6)\\
&First\ Stage: && \Delta LTRshare_{it} = \alpha IV_{it} + \boldsymbol{X}'_{it}\mu + \epsilon_{it}, && (7)\\
&Reduced\ Form: && Y_{it} = \tilde{\beta} IV_{it} + \boldsymbol{X}'_{it}\tilde{\Gamma} + \tilde{\varepsilon}_{it}. && (8)
\end{aligned}$$

In equation 6, the coefficient β denotes the OLS estimate of the effect of $\Delta\text{LTRshare}_{it}$, the Z-score of the annual change in the share of single-family homes owned by larger LTRs in a given year t relative to year $t-1$, on Y_{it}, the housing market outcome in Census Tract i in year t. On the equation's right-hand side, we control for baseline 2010-level socioeconomic and demographic Tract characteristics and the interaction of county and year fixed effects, encapsulated by the vector $\boldsymbol{X}_{it}$. The baseline controls also incorporate the housing supply elasticity at the Tract level, as estimated by Baum-Snow and Han (2023) 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, we 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 to capture unobservable temporal variations in housing market conditions across counties due to regional cycles.

Equation 7 details the first-stage regression that estimates the relationship between our instrument, IV_{it}, and the Z-score of the actual change in LTR share, $\Delta\text{LTRshare}_{it}$. Equation 8 presents the reduced form regression, where the coefficient $\tilde{\beta}$ quantifies the direct impact of the instrument on the housing market outcome. The two-stage least squares (2SLS) estimation coefficient is derived by dividing $\tilde{\beta}$ by δ. In Equations 7 and 8, $\boldsymbol{X}_{it}$ include the housing supply elasticities, boom and bust dynamics, and county-by-year fixed effects, but not the baseline Tract characteristics as our instrument is built already orthogonalized with respect to these characteristics. 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.

Figure 9: Placebo Check: Pre-period Price Changes against Suitability Index



Notes: This figure shows the binned scatterplot of total house price changes between 2000 and 2009 against our Suitability Index, S_i, controlling for county fixed effects and local house price elasticities of supply from Baum-Snow and Han (2023).

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 instrument for changes in LTR market share must be orthogonal to omitted characteristics that are correlated with changes in housing market outcomes, conditional on the specified baseline Census Tract characteristics and fixed effects. This identifying assumption can be formally stated as:

$$\mathbb{E}[IV_{it} \times \tilde{\varepsilon}_{it} | \boldsymbol{X}_i] = 0. \tag{9}$$

Although this assumption cannot be directly tested, we provide corroborating evidence that our instrument is uncorrelated with unobserved determinants of local housing market changes. Specifically, we perform a placebo test for pretrends between 2000 and 2009 in the decade before the rise of LTRs, following suggestions by Goldsmith-Pinkham et al. (2020). The intuition is that we should not see differential changes in house prices and rents for locations suitable vs. unsuitable for LTRs in the period before the concurrent rise of LTRs and OPM software.

Figure 9 provides a visual check that, indeed, there is no statistical relationship between house price growth in the pre-period and our instrument, conditional on county fixed effects and Tract level house price elasticity of supply controls. Our binned scatterplot plots an average price change of about 27% over the period, and Tracts with varying suitability differ by at most 5% in their overall price growth, suggesting a minimal economic or statistical impact of the suitability index on pre-trends in housing prices. This placebo check suggests balance in our left-hand side variables with respect to our instrument, mitigating concerns that selection or omitted factors influencing price changes survive our instrument construction.

5 House Price Results

We estimate equations 6, 7, and 8 in a changes-on-changes specification, consistent with the canonical examples in Bartik (1991) and Blanchard and Katz (1992). The variation exploited 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 in *levels*, while assuming the baseline shares are exogenous to *changes* in the outcome variable (Goldsmith-Pinkham et al., 2020). 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.[18] 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.

Endogenous OLS Results

We begin by running the endogenous OLS specification outlined in Equation 6, presented in Table 4. Column (1) shows the results of estimation on our full sample of Tracts, regardless of whether they saw positive LTR market share growth over the sample period. This allows us to incorporate information from Tracts where LTRs entered and subsequently decided to leave. The coefficient of interest, β, equals 0.149 and is statistically significant at the 1% level. Interpreting this coefficient, if Tract A experiences an annual change in LTR market share (measured in the Z-score of annual changes to accommodate the long right tail) that is a 1-standard deviation higher than Tract B, house price growth in Tract A would exceed that in Tract B by 0.149 percentage points (pp). This implies an elasticity of a 1.16pp higher house price growth (dividing the point estimate by the sample standard deviation in annual change in LTR market share which is 0.128pp) per 1pp increase in LTR share change. This reflects an acceleration in house price growth of 32% (=1.16/3.670) relative to a Tract that experiences an average house price growth of 3.67pp. We note that only about 2,100 of our approximately 30k tracts ever see LTR market share reach 1pp by 2022, so this elasticity in practice is much lower when applied to mean LTR market share.

As discussed in Section 4.1, we would expect these results to be biased if trends in house price growth attracted LTRs to these locations (reverse causality), or attenuated towards zero if we are mismeasuring LTR share, which is likely due to the inability to link all investor-owned properties

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

back to a limited set of firms.

As we move from left to right across the columns, we restrict our sample of Tracts to those with significant LTR presence. We do so to remove Tracts that never see LTR entry from the sample, leveraging *intensive* margin variation in entry rather than *extensive* margin variation. This has the benefit of cutting down on the noise introduced by particularly unsuitable tracts (i.e. those in rural areas, or with primarily high-rise multifamily rentals), at the cost of a more narrow interpretation of our price impacts.

Column (2) of Table 4 shows that the price impact of an additional standard deviation increase in LTR market entry falls relative to Column (1). Conditional on a Tract having positive LTR presence by 2022, LTRs seem to explain less of the annual price growth than in the full sample. Moving to Column (3), we find that in Tracts where LTRs own at least 1% of the single-family housing stock (both rental and owner-occupied), they can explain even less of the annual price change. Column (4) presents results conditioning on Tracts in which LTRs owned at least 10 units, rather than a local share, and again we find the results smaller than estimated in Column (1). These results are consistent with LTRs selecting into faster HPI growth tracts, where a marginal increase in their presence explains much less of the residual variation in price changes. In sum, controlling for having selected into a subset of Tracts, we find that additional variation in LTR entry puts much less pressure on house prices, suggesting selection biases the point estimates in column (1) upwards. On the other hand, even with sample restrictions, we are not able to explore whether unobserved local shocks (simultaneity) or measurement error contributes to any meaningful downward bias in the point estimates. Thus, we turn to the two-stage least squares results.

First Stage Results

We next implement the specification outlined in Equation 7 and present results in Table 5, Panel A. Working across the columns we move from less- to more-restricted samples as in Table 4. In Column (1), we see that a 1 standard deviation increase in the change in IV induces an increase in the change in LTR market share of 0.0382 standard deviations, statistically significant at the 1% level. Given a sample standard deviation of 0.128pp for change in LTR market share, this implies an increase relative to a Tract that experiences a mean ΔLTR of $0.0382 \times 0.128/0.0196 = 25\%$; in short, a 1 standard deviation increase in annual ΔIV predicts 25% faster LTR growth. The first stage F-statistics is above 43, suggesting a strong first stage.

As we move across the columns and restrict our sample of tracts, we find that the instrument has a larger impact on annual LTR entry, and the Tracts have higher baseline LTR growth. This is consistent with the observation that LTRs tend to concentrate their holdings in specific tracts; as costs fall over time, LTRs move more intensively to more suitable Tracts. As we move from column (1) to column (3), we see that the mean change in LTR share increases from 0.0196 to 0.199, while the point estimate increases from 0.0382 to 0.0844. Applying the same algebra as above, in these Tracts, a 1 standard deviation increase in annual ΔIV predicts 16% faster LTR growth. The stability of the IV's impact on LTR growth across subsamples corroborates that our

Table 4: Endogenous OLS Results: *House Prices*

	Dependent Variable: $\Delta \text{HPI}_{\text{FHFA}}(\%)$			
	(1) Full Sample	(2) Δ LTR $\geq$ 0%	(3) LTR $\geq$ 1% in 2022	(4) LTR $\geq$ 10 Units in 2022
Z-score Δ LTR Share (%)	0.149***	0.097***	0.055**	0.057**
	(0.035)	(0.027)	(0.023)	(0.024)
Δ FHFA HPI 00-06 (%)	0.018***	0.017***	0.011***	0.014***
	(0.001)	(0.002)	(0.003)	(0.002)
Δ FHFA HPI 06-10 (%)	-0.026***	-0.034***	-0.032***	-0.030***
	(0.006)	(0.007)	(0.008)	(0.008)
Controls Measured at 2010 Baseline				
Log Rent	0.015***	0.001	-0.028*	-0.031*
	(0.006)	(0.007)	(0.016)	(0.018)
Log Home Value	-0.563***	-1.214***	-1.688***	-1.656***
	(0.131)	(0.112)	(0.118)	(0.120)
Log Income	0.030	-0.141**	-0.119	-0.023
	(0.111)	(0.071)	(0.097)	(0.090)
Vacancy	-0.012	0.043	-0.555	-0.784***
	(0.194)	(0.245)	(0.338)	(0.279)
College	0.105	0.758***	0.379*	0.332*
	(0.146)	(0.202)	(0.205)	(0.196)
Unemployment	0.645***	0.324	-0.576	-0.314
	(0.201)	(0.264)	(0.509)	(0.442)
Poverty	0.721**	0.296	-0.354	-0.157
	(0.283)	(0.315)	(0.246)	(0.273)
Non-Hispanic Black	0.458***	0.354*	0.342*	0.311*
	(0.152)	(0.190)	(0.185)	(0.179)
Asian	0.261	0.291	1.115**	0.821
	(0.335)	(0.511)	(0.560)	(0.552)
Hispanic	1.396***	1.117**	1.990***	1.967***
	(0.323)	(0.464)	(0.406)	(0.335)
Housing Supply Elasticity	-0.339***	-0.233***	-0.404***	-0.392***
	(0.052)	(0.070)	(0.080)	(0.076)
Observations	384,348	129,348	26,592	34,836
R-squared	0.679	0.726	0.746	0.753
County $\times$ Year FE	Y	Y	Y	Y
Dep. Var. Mean (%)	3.670	4.364	5.046	4.905
Dep. Var. SD (%)	6.578	7.137	7.815	7.692

Notes: This table runs the specification outlined in Equation 3, regressing changes in house price indices on changes in LTR market shares. The panel spans Census Tracts between 2010–2022. Column (1) shows the effects for the full sample, Columns (2) and (3) condition on Tracts with increasingly large LTR shares by 2022, and Column (4) conditions on Tracts in which LTRs hold at least 10 units. We control for socioeconomic and demographic factors in 2010, house price dynamics over the preceding boom (2000-2006) and bust (2006-2010) eras, as well as Tract level house price elasticity of supply from Baum-Snow and Han (2023). All standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

instrument is uncorrelated with omitted variables that are driving selection into specific Tracts.

As for other drivers of LTR entry, they tend to avoid Census Tracts that are highly elastically supplied, suggesting they do not want competition from new supply driving down rents. Additionally, LTRs tend to enter faster in areas with less price volatility over the previous housing boom-bust cycle, suggesting they favor stable price growth.

Two Stage Least Squares Results

Finally, we implement the specification discussed in Section 4.5, dividing the reduced form estimates by the first stages. We present results in Table 5, Panel B. Working across the columns we move from less- to more-restricted samples as in Table 4. In Column (1), we see that a 1 standard deviation increase in instrumented annual LTR change induces an increase in the HPI change of 3.24, statistically significant at the 1% level.

Moving on to column (2), which leverages *intensive* margin variation in LTR share growth, excluding the sample of Tracts that never see LTR entry, we find that our point estimate falls by over half, to 1.26, statistically significant at the 1% level. Interpreting the point estimate, a 1pp increase in the change in LTR share would induce an 6.20pp (=1.2646/0.204) higher house price growth, confirming that measurement error and simultaneity contributed to a downward bias in the endogenous OLS specifications. We again note that a 1pp increase in LTR share over one year is large; a Tract experiencing a 1 standard deviation above the mean change in LTR share would only realize a 0.2621pp (=0.204+0.0581) annual change in LTR share, implying a 1.63pp higher growth in house prices.

Again for other drivers of house price growth, we see less price growth in elastically supplied Census Tracts, as expected. Places that boomed in the previous decade experienced higher annual house price growth between 2010 and 2022 as well; while locations that busted more see less annual price growth, though these results are less precisely estimated across our specifications.

6 Rent Results

We now move on to discussing the rise of LTRs on market rents. In contrast to the price results, we might expect rent results to be more attenuated; while LTRs help bid up house prices acting as new bidders, and remove potential owner-occupant stock contributing to lower inventory for that cohort, they expand the set of rental units in a given geography. We discuss in more details the implications of competing forces in Section 7.

For our rent analysis, we rely on data from Zillow's Observed Rent Index between 2015 and 2022. To keep the interpretation of these point estimates as consistent as possible, we estimate Equations 3 and 7, as well as those discussed in Section 4.5 using as our left-hand-side variable the percent change in ZORI, which is denominated in dollars, denoted by ΔZORI (%). This is more consistent with changes in the house price index which we use for the house price results in Section 5.

Table 5: First Stage and 2SLS Results: *House Prices*

Panel A: First Stage

Dep. Var: Z-score Δ LTR	(1) Full Sample	(2) Δ LTR ≥ 0%	(3) LTR ≥ 1% in 2022	(4) LTR ≥ 10 Units in 2022
Δ IV	0.0382***	0.0763***	0.0844***	0.0892***
	(0.006)	(0.011)	(0.030)	(0.024)
Δ FHFA HPI 00-06 (%)	-0.0025***	-0.0049***	-0.0073***	-0.0074***
	(0.001)	(0.001)	(0.003)	(0.002)
Δ FHFA HPI 06-10 (%)	-0.0090***	-0.0185***	-0.0266***	-0.0270***
	(0.001)	(0.003)	(0.005)	(0.005)
Housing Supply Elasticity	-0.0429***	-0.0449*	-0.1088	-0.1568***
	(0.013)	(0.026)	(0.076)	(0.057)
Observations	384,348	129,348	26,592	34,836
R-squared	0.247	0.280	0.402	0.365
First Stage F-Stat	43.61	45.64	7.757	14.19
County × Year FE	Y	Y	Y	Y
Δ LTR Mean (%)	0.0196	0.0581	0.199	0.163
Δ LTR S.D. (%)	0.128	0.204	0.383	0.347

Panel B: 2SLS

Dep. Var: ΔHPI_{FHFA} (%)	(1) Full Sample	(2) Δ LTR ≥ 0%	(3) LTR ≥ 1% in 2022	(4) LTR ≥ 10 Units in 2022
Z-score Δ LTR Share	3.2431***	1.2646**	1.7782	0.9392
	(0.999)	(0.508)	(1.200)	(0.814)
Δ FHFA HPI 00-06 (%)	0.0296***	0.0267***	0.0288***	0.0261***
	(0.003)	(0.003)	(0.010)	(0.008)
Δ FHFA HPI 06-10 (%)	-0.0182*	-0.0407***	-0.0198	-0.0432*
	(0.010)	(0.011)	(0.034)	(0.026)
Housing Supply Elasticity	-0.5503***	-0.6292***	-0.4332**	-0.5162***
	(0.087)	(0.112)	(0.202)	(0.180)
Observations	384,348	129,348	26,592	34,836
RMSE	3.944	3.806	4.409	3.927
County × Year FE	Y	Y	Y	Y
Dep. Var. Mean (%)	3.670	4.364	5.046	4.905
Dep. Var. SD (%)	6.578	7.137	7.815	7.692

Notes: This table runs the specification outlined in Equation 7 and the two-stage least squares estimation discussed in Section 4.5. The panel spans Census Tracts between 2010–2022. Column (1) shows the effects for the full sample, Columns (2) and (3) condition on Tracts with increasingly large LTR shares by 2022, and Column (4) conditions on Tracts in which LTRs hold at least 10 units. We control for house price dynamics over the preceding boom (2000-2006) and bust (2006-2010) eras, as well as Tract level house price elasticity of supply from Baum-Snow and Han (2023). All standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Before moving on to our results, we first identify three caveats of using the ZORI. First, Zillow does not provide a balanced panel of zip codes with ZORIs; instead, the sample of zip codes with available ZORIs increases over time. Second, the zip codes with available ZORIs tend to be more urban and suburban than those in the house price panel, which is more geographically comprehensive. Third, we only observe ZORI for the unbalanced panel of zip codes from 2015 onwards.[19] This means that the price and rent results are identified off different samples, both geographically and temporally, differences we are continuing to explore. In Appendix Section B, we discuss these caveats in more detail, and conclude that there is no statistically significant relationship between LTR share, in levels or in changes, and entry into the ZORI panel. This mitigates concerns that any differential sample selection is correlated with our endogenous variable.

Endogenous OLS Results

Table 6 displays the results of estimating our endogenous ordinary least squares specification. The columns follow the same sample selection as in the house price results, with column (1) using the full sample of our available crosswalked ZORI zip codes to census tracts. Columns (2), (3), and (4) impose increasingly stringent LTR entry on the estimation sample.

Starting with Column (1) of Table 6, we see the estimated coefficient of interest, β, equals 0.016 and is not statistically significant. A generous interpretation would imply that a tract shocked with a 1-standard deviation increase in the change of LTR market share in a given year would realize an additional rent growth of 0.016pp. This implies a rent elasticity w.r.t. LTR entry of 0.07 (dividing the point estimate by the sample standard deviation in annual change in LTR market shares, which is 0.218pp). Given the average tract in our sample experiences an annual rent growth of about 5.7%, these results suggest little impact of LTR entry on rents, both economically and statistically. Moving across the other columns, we do not see much change; in the endogenous rent estimation, LTRs do not impact rents measurably, either on the extensive margin or intensive margin samples. This could be because LTRs select into areas already experiencing rising rents (reverse causality), or that we are mismeasuring LTR entry, the same identification concerns we would expect in the house price regressions.

First Stage Results

We next re-estimate Equation 7; while the first stage method has not changed, the sample of tracts has and so we present the relevant first stage in Table 7, Panel (A). Two causes for concern could potentially change the interpretation of our first-stage results. First, our observation count is much lower in the sample of tracts with available ZORI data relative to the sample with available HPI data, highlighting the differences in geographic coverage. If the ZORI data sample focuses on more suburban or urban areas where LTRs had more entry, we may see LTR entry becoming more responsive to our IV in the first stage. Second, LTR entry became more responsive to our IV in the later sample period; by removing the period between 2010 and 2014 (wherein ZORI is not available) in which industry growth was uncertain, we focus on the next era of LTR entry,

[19] more details in the footnote associated with the ZORI data discussion in Section 2.

Table 6: Endogenous OLS Results: *Rents*

	Dependent Variable: ΔZORI (%)			
	(1)	(2)	(3)	(4)
	Full Sample	Δ LTR ≥ 0%	LTR ≥ 1% in 2022	LTR ≥ 10 Units in 2022
Z-score Δ LTR Share (%)	0.016	0.018	0.021	0.023
	(0.026)	(0.021)	(0.014)	(0.017)
Δ FHFA HPI 00-06 (%)	0.000	-0.000	-0.001	0.001
	(0.002)	(0.002)	(0.004)	(0.003)
Δ FHFA HPI 06-10 (%)	-0.024***	-0.030***	-0.028***	-0.029***
	(0.005)	(0.006)	(0.009)	(0.009)
Controls Measured at 2010 Baseline				
Log Rent	-0.037*	-0.038**	0.013	-0.011
	(0.021)	(0.018)	(0.041)	(0.031)
Log Home Value	-0.089	-0.115	-0.396**	-0.133
	(0.111)	(0.134)	(0.158)	(0.120)
Log Income	-0.114	-0.402***	-0.246**	-0.384***
	(0.140)	(0.151)	(0.115)	(0.140)
Vacancy	1.879**	1.183***	0.542	0.551
	(0.845)	(0.415)	(0.454)	(0.464)
College	-0.685**	0.094	0.107	0.019
	(0.315)	(0.293)	(0.327)	(0.332)
Unemployment	0.838*	0.078	0.468	0.989*
	(0.442)	(0.504)	(0.613)	(0.595)
Poverty	-0.300	-0.371	0.203	0.084
	(0.285)	(0.334)	(0.390)	(0.404)
Non-Hispanic Black	0.010	0.273	0.048	0.238
	(0.301)	(0.342)	(0.342)	(0.311)
Asian	-1.299***	-2.462***	-1.206	-2.342***
	(0.443)	(0.645)	(1.120)	(0.714)
Hispanic	-0.781**	-0.232	0.368	0.238
	(0.379)	(0.394)	(0.420)	(0.445)
Housing Supply Elasticity	0.312**	-0.019	0.239	0.233
	(0.139)	(0.125)	(0.237)	(0.162)
Observations	46,894	22,712	8,469	34,836
R-squared	0.770	0.809	0.872	0.753
County × Year FE	Y	Y	Y	Y
Dep. Var. Mean (%)	5.716	6.469	6.862	4.905
Dep. Var. SD (%)	4.258	4.302	4.257	7.692

Notes: This table runs the specification outlined in Equation 3, regressing percent changes in rents on changes in LTR market shares. The panel spans ZORI data from 2015–2022 (annual changes from 2016–2022), which we've crosswalked to Census Tracts. Column (1) shows the effects for the full sample, Columns (2) and (3) condition on Tracts with increasingly large LTR shares by 2022, and Column (4) conditions on Tracts in which LTRs hold at least 10 units. We control for socioeconomic and demographic factors in 2010, house price dynamics over the preceding boom (2000-2006) and bust (2006-2010) eras, as well as Tract level house price elasticity of supply from Baum-Snow and Han (2023). All standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

characterized by steady growth in market share, as shown in Figure 5.

As in the house price results, the columns in Table 7 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 0.0578 standard deviations, of similar magnitude to the house price results (the respective point estimate in the house price sample is 0.038 standard deviations). In this sample, a tract with a 1-standard deviation increase in our IV would experience an additional $0.218 \times 0.0578/0.0476 = 26.5\%$ faster LTR growth, given the sample mean and standard deviation of ΔLTR. These results are comparable to the first stage house price results (25% faster LTR growth).

Moving across the columns in Table 7, Panel A, we again see increased coefficients, but their impacts rely on the changing sample mean and standard deviation of LTR growth. Moving across the columns and applying the same algebra above, we see that a 1-standard deviation increase in our IV translates to a 21–29% faster LTR growth, again comparable to our house price results (16–27% faster LTR growth), suggesting the samples are not so different as to meaningfully change our first stage conclusions relative to the house price sample.

Two Stage Least Squares Results

Panel B of Table 7 shows the second stage results with percent change in rent as the dependent variable. In contrast to the endogenous OLS, in the full sample, we see larger impacts on rents: a 1-standard deviation increase in annual LTR entry accelerates the rent growth by 4.013pp, significant at the 1% level.

Similar to the price results, the impact of a 1-standard deviation increase in LTR market share growth is *smaller* when we move to the intensive margin sample in Column (2). A 1-standard deviation increase in annual LTR share change implies a 1.642pp increase in rent growth or about 25% additional annual rent growth. Moving towards an elasticity, a 1pp increase in the change in LTR share would induce a 5.47pp (=1.642/0.300) higher rent growth, confirming that measurement error and simultaneity contributed to a downward bias in the endogenous OLS specifications. We again note that a 1pp increase in LTR share over one year is large; in the rent sample, a tract experiencing a 1 standard deviation above the mean change in LTR share would only realize a 0.401pp (=0.101+0.300) annual change in LTR share, implying a 2.19pp higher growth in rents.

This column limits analysis to only those tracts with positive LTR presence in 2022, identifying the impact of *intensive* margin increases in LTR share, rather than the *extensive* margin selection into a location. Comparing columns (1) and (2) suggests that rents respond to increased market share nonlinearly.

Finally, moving to the right tail census tracts, those with significant market entry by 2022, we see little to no rent response, which could suggest the change in rental supply put downward pressure on rents even as LTR share rose. We discuss this possibility more in the next section.

Table 7: First Stage and 2SLS Results: *Rents*

Panel A: First Stage

Dep. Var: Z-score Δ LTR	(1) Full Sample	(2) Δ LTR ≥ 0%	(3) LTR ≥ 1% in 2022	(4) LTR ≥ 10 Units in 2022
Δ IV	0.0578***	0.0990***	0.1106***	0.1149***
	(0.010)	(0.014)	(0.026)	(0.023)
Δ FHFA HPI 00-06 (%)	-0.0044***	-0.0056***	-0.0023	-0.0033
	(0.001)	(0.002)	(0.002)	(0.003)
Δ FHFA HPI 06-10 (%)	-0.0152***	-0.0252***	-0.0225***	-0.0252***
	(0.004)	(0.005)	(0.005)	(0.005)
Housing Supply Elasticity	-0.0610	-0.0054	0.0384	-0.0116
	(0.060)	(0.087)	(0.147)	(0.121)
Observations	46,894	22,712	8,469	10,430
R-squared	0.347	0.355	0.397	0.367
First Stage F-Stat	33.40	48.03	18.60	24.40
County × Year FE	Y	Y	Y	Y
Δ LTR Mean (%)	0.0476	0.101	0.234	0.199
Δ LTR S.D. (%)	0.218	0.300	0.443	0.410

Panel B: 2SLS

Dep. Var: ΔZORI (%)	(1) Full Sample	(2) Δ LTR ≥ 0%	(3) LTR ≥ 1% in 2022	(4) LTR ≥ 10 Units in 2022
Z-score Δ LTR Share	4.0133***	1.6418***	0.3848	0.3547
	(1.260)	(0.598)	(0.539)	(0.405)
Δ FHFA HPI 00-06 (%)	0.0202***	0.0117**	0.0034	0.0047
	(0.007)	(0.006)	(0.005)	(0.004)
Δ FHFA HPI 06-10 (%)	0.0353**	0.0067	-0.0327	-0.0341**
	(0.015)	(0.016)	(0.020)	(0.017)
Housing Supply Elasticity	0.2167	-0.3678*	-0.0231	-0.0347
	(0.324)	(0.208)	(0.260)	(0.405)
Observations	46,894	22,712	8,469	10,430
RMSE	3.585	2.471	1.609	-0.041
County × Year FE	Y	Y	Y	Y
Dep. Var. Mean (%)	5.716	6.469	6.862	6.764
Dep. Var. SD (%)	4.258	4.302	4.257	4.292

Notes: This table runs the specification outlined in Equation 7 and the two-stage least squares estimation discussed in Section 4.5. The panel spans Census Tracts between 2015–2022. Column (1) shows the effects for the full sample, Columns (2) and (3) condition on Tracts with increasingly large LTR shares by 2022, and Column (4) conditions on Tracts in which LTRs hold at least 10 units. We control for house price dynamics over the preceding boom (2000-2006) and bust (2006-2010) eras, as well as Tract level house price elasticity of supply from Baum-Snow and Han (2023). All standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

7 Potential Mechanisms and Further Work

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).

First, we walk through the implications of the *professionalization* mechanisms. Calder-Wang and Kim (2023) find that the adoption of algorithmic pricing in rental markets leads to landlords extracting more rents from tenants as they adjust prices more dynamically. This suggests that the reallocation of 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 as well as 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 type of reallocation would put more price pressure on single-family housing, as more bidders enter the market (investors and owner-occupants), and since it takes time to build new stock, these bidders would compete over smaller single-family inventories. While prices rise due to this mechanism, this source of reallocation will lower observed rents as the rental supply expands.

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.

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 three reallocation mechanisms (excluding build-to-rent) point to a series of testable hypotheses we plan to take to the data:

1. Prices rise due to reallocation of stock from small to large landlords, and due to reallocation of stock from owner-occupants to investors.

2. Rents will fall if the driving mechanism is an expansion of the rental supply (through reallocation or new building)

3. Rents will rise if the driving mechanism is the professionalization of the rental market, the adoption of responsive algorithmic pricing, or increased market power

Importantly, which hypothesis drives our results can be context-specific. For example, the expansion of the rental supply surged between 2012 and 2015 when LTRs had to buy from other investors or owner-occupants before major mergers and acquisitions began to take place. This means we would expect different rent results based on the period of study, and potentially stronger price results over time as these mechanisms stack on top of one another.

All of these mechanisms require measurement of reallocation between small landlords, large landlords, owners, and builders. As a first step, Table 8, shows the transition matrices of housing transactions between different seller and buyer types. Each cell in the table is the percentage of all single-family or townhouse transactions with a given seller-buyer pair type. For example, the top-left cell in each panel shows the percent of transactions sold by an "Other Investor" (one that is not a short-term investor and not an LTR, an aggregation of all of our smaller landlords) to another "Other Investor." We present these transition matrices for all Tracts in Panel A, as well as those that end up attracting the highest shares of LTR entry by 2022 in Panel B.

For all Tracts, we see that the most transactions occur between owner-occupants to other owner-occupants, at 73% of the total. The next largest transaction pairs occur between other investors and owner-occupants: 11% of transactions are owner-occupants selling to other investors, and 12% are other investors selling to owner-occupants. Builders supplying new stock only contribute about 0.2% of total transactions, and they split their sales mostly between other investors and owner-occupants. Lastly, LTRs make up a small share of transactions over our 13-year sample, acting as sellers in about 0.2% of all transactions, and as buyers in 0.5% of transactions nationally, consistent with their holding about 0.36% of the single-family and townhome stock by 2022. Aggregating across buyers and sellers, we expect that other investors on net sold properties (seller % - buyer % = 1.7% net seller), as did builders (net sales of 0.16% of transactions), which provide a good sanity check since builders are in the business of transforming existing land or properties into more housing supply. On the other hand, owner-occupants and LTRs gained stock on the net, with owner-occupants net-buying 1.6% of transactions, and LTRs net-buying 0.31% of transactions. These findings are in line with the LTR industry growth, as well as the homeownership surge during and following the COVID-19 pandemic.

In sum, on a national level, we see evidence of all three reallocation stories discussed above. First, other investors sell to LTRs more often than LTRs sell to other investors, suggesting landlord professionalization as stock is reallocated from small to large landlords. Second, owner-occupants sell more to LTRs than do LTRs to owner-occupants, showing the reallocation of the housing stock from owner-occupants to the rental market. Third, builders supply new housing, though they don't tend to sell to LTRs as often as other buyer types.

Focusing on those Tracts with significant LTR entry between 2010 and 2022, we see stronger reallocation. Owner-occupant to owner-occupant transactions still make up the largest portion of transactions, but this share falls to 64%, relative to 73% in the national data. Trades between owner-occupants and other investors remain stable across the two samples, totalling 23% in the national sample, and 25% in the top LTR share sample. While trades among owner-occupants and between owner-occupants and other investors in total decline, LTRs now comprise nearly 5% of all purchasers. They comprise only 1.71% of all sellers, and the majority of these homes transact *between* LTRs: conditional on an LTR being a seller, 83% of its sales are to other LTRs. In contrast, LTRs buy in similar magnitudes from both other investors and owner-occupants. The result is a reallocation of stock, both previously rented and owned, to the LTRs, after which it most often becomes traded *within* LTRs, staying in the professionalized rental market.

In these LTR concentrated Tracts, we see an increasing reallocation of housing stock from owner-occupants to rentals, in particular to LTRs who gain on net 3.12% of transactions. Owner-occupants and other investors sell on the net, at 1% and 2% respectively, along with builders who supply a small share of new units. In these Tracts, we see significantly more reallocation between small landlords and LTRs, with LTRs buying 10 times more transactions than they sell to other investors. We also see evidence of reallocation of the rental stock; while owner-occupants on net buy more from other investors than they sell, this is only about 0.6% of all transactions. In contrast, owner-occupants on net sell much more to LTRs than they buy, on net selling 1.67% of transactions (12 times the transactions on which they were on the buy side).

In further work, we plan to analyze mean *property level* price and rent changes by buyer-seller types to help disentangle which mechanisms enumerated above may be driving the house price changes estimated in the Tract-level samples. I.e. how do house-level prices evolve when a house is sold by an owner occupant vs. a small landlord to a LTR? How do rents evolve when a house is traded between small landlords and LTRs? Between two LTRs? Additionally, in Tract-level analysis we intend to construct Tract-level measures of reallocation between the landlords types, reallocation between owner-occupants and the rental market, and new building in conjunction with a local rental price index constructed from Multiple Listing Service data to test the three hypotheses enumerated above. Comparing the house-specific price and rent changes relative to the market-level changes will help illuminate the competing, or compounding mechanisms.

8 Conclusion and Further Work

Since the Great Recession, the rise of single-family rental companies has changed the investor ownership landscape in the U.S. Using housing transaction data, we document the rise of Long Term Rental (LTR) companies by constructing a panel of national single-family housing portfolios. We show that LTR growth outstripped all other investor types and that these companies geo-

Table 8: Ownership Transition Matrix

Panel A: All Tracts

		Seller Type				
		Other Investor	LTR	Builder	Owner Occupants	Total
Buyer Type	Other Investor	3.268	0.025	0.023	10.668	13.984
	LTR	0.165	0.153	0.005	0.207	0.531
	Builder	0.022	0.001	0.006	0.032	0.060
	Owner Occupants	12.231	0.042	0.186	72.966	85.425
	Total	15.686	0.221	0.220	83.873	100.000

Panel B: Tracts with Top 5 Percentile LTR Entry by 2022

		Seller Type				
		Other Investor	LTR	Builder	Owner Occupants	Total
Buyer Type	Other Investor	4.84	0.15	0.05	12.51	17.56
	LTR	1.56	1.40	0.05	1.82	4.83
	Builder	0.05	0.01	0.02	0.09	0.17
	Owner Occupants	13.08	0.15	0.30	63.91	77.44
	Total	19.53	1.71	0.42	78.34	100.00

Notes: These transition matrices show the share of transactions with buyer types indicated by the left-column options $\in$ {Other Investor, LTR, Builder, Owner Occupants and seller types listed in table column headers. Cells populated with the total percent of all transactions attributable to a seller type - buyer type pair. The sample includes all transactions of single-family homes or townhomes in our CoreLogic sample from 2010–2022. Authors' calculations based on owner classifications discussed in Section 2.

graphically concentrate their holdings, expanding their local market shares over time. LTRs prefer newer, mid-size, single-family units relative to more traditional small landlords (SLLs), earning their moniker as "Single Family Renters," though many of our LTR investors' primary activity is Private Equity Real Estate (PERE). LTRs target neighborhoods with healthy rental markets, low vacancies, and low poverty that also have higher minority shares, consistent with concerns about concurrent gentrification.

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.

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*, Accepted, 2023.

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.

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.

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

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 opportuntiy? Evidence from the Great Migration. *American Economic Review*, 112:369–408, 2022.

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.

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.

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.

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.

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.

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.

A Data Construction Appendix

A.1 Ownership Imputation: A Canonical Example

Below is an example to illustrate how we impute the ownership for each property in each year between 2000 and 2022. The CoreLogic data reports three historical transactions in 1998, 2005, and 2021 as well as the latest tax assessment record. For example, the property was sold from A to B in 1998. The tax assessment year is usually 2022 or 2021 with very few exceptions reported for years prior to 2021, so it contains the most up-to-date information on who owns the property.

- 1998: A $\rightarrow$ B
- 2005: C $\rightarrow$ D
- 2021: E $\rightarrow$ F
- The latest tax: G is the owner

Below is the imputed ownership for this property. In most cases, the current buyer (e.g., B) is the same as the next seller (e.g., C). In case this is not true, we prioritize using the buyer's information to impute ownership. Following our imputation rules, the property was owned by B from 2000 to 2004, by D from 2005 to 2020, and by F if the tax year is 2021 or earlier than 22021, and by G if the tax year is 2022.

- 2000-2004: B
- 2005-2020: D
- 2021-2022:
  - F, if the latest tax year is 2021 or earlier than 2021
  - G, if the latest tax year is later than 2021

Our general imputation rules are below:

- Only keep the latest transaction before 2000 and the transactions during 2000-2022
- Prioritize using buyer information to impute ownership
- Use seller information (from deed) to back out the owner of a property in the first year(s)
- Use buyer information (from deed) to fill in ownership in between transaction years
- Use buyer information (from tax) to back out the ownership of a property in the latest year(s)
- If both the year built and the first transaction year are after 2000, only keep years after the year built (the first transaction year) if year built $\leq$ ($\geq$) the first transaction year

A.2 Ownership Imputation: A Real (Anonymized) Example

Table A1 shows two real transaction records for a property in Baldwin County, Alabama whose unique property identifier is 00413XXXX and whose year built is 1994. "Anonymous 3 & Cosigner B" is reported as the owner in the latest tax year 2021. Table A2 shows the ownership after the imputation for this property from 2000 to 2022.

Table A1: Transaction Records

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

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

A.3 Price Imputation: An Example

Table A1 shows an example of imputing fair market values for the aforementioned property from 2000 to 2022. We impute fair market prices for this property based on the actual prices of the two transactions and the total growth rate of HPIs (rounded) produced from the hedonic regressions. For example, the fair market price in 2003 is \$432,531 (= \$403,520*1.08).

Table A3: Price Imputation

Year	Owner	Transaction Price	HPI Growth	Imputed Price
2000	Anonymous 1		1.11	368,157
2001	Anonymous 1		1.01	371,942
2002	Anonymous 2 & Cosigner A	403,520	1.08	403,520
2003	Anonymous 2 & Cosigner A		1.07	432,531
2004	Anonymous 2 & Cosigner A		1.33	577,034
2005	Anonymous 2 & Cosigner A		0.93	541,389
2006	Anonymous 2 & Cosigner A		0.93	507,946
2007	Anonymous 2 & Cosigner A		0.93	476,569
2008	Anonymous 2 & Cosigner A		0.94	451,611
2009	Anonymous 2 & Cosigner A		0.94	427,960
2010	Anonymous 2 & Cosigner A		0.94	405,548
2011	Anonymous 2 & Cosigner A		0.97	393,944
2012	Anonymous 2 & Cosigner A		0.97	382,672
2013	Anonymous 2 & Cosigner A		0.97	371,722
2014	Anonymous 2 & Cosigner A		1.29	480,957
2015	Anonymous 2 & Cosigner A		0.98	472,788
2016	Anonymous 3 & Cosigner B	331,946	1.05	331,946
2017	Anonymous 3 & Cosigner B		1.06	353,513
2018	Anonymous 3 & Cosigner B		0.99	351,362
2019	Anonymous 3 & Cosigner B		1.07	379,023
2020	Anonymous 3 & Cosigner B		0.94	356,907
2021	Anonymous 3 & Cosigner B		1.24	442,839
2022	Anonymous 3 & Cosigner B		1.08	482,450

A.4 Identifying Chunky Transactions

We identify chunky transactions as those transactions that happened on the same day, at the same abnormally high price, and associated with the same buyer. We fill in hedonic-imputed prices for these chunky transactions.[20] These chunky transactions are typically associated with institutional buyers such as builders and rental companies that buy tens or hundreds of properties all at once. Table A4 shows two cases in which all properties were purchased by the same buyer on the same day.[21] For example, Construction Firm LLC bought eighteen properties from Firm A LLC for $6,120,000 on October 19, 2006. Rental Firm LLC purchased thirty-five properties for $9,275,000 from Holding Company LLC on July 28, 2006.

Instead of using the reported prices that seem problematic, we use the hedonic-imputed prices as the transaction prices for these chunky transactions.[22] The hedonic-imputed prices are calculated as the sum of the product between the property-level characteristics and county-level coefficients estimated from the hedonic regressions.

A.5 Identifying Subsidiaries of Publicly-Listed and Private Firms

Table A5 and Table A6 list several examples to explain how we identify the subsidiaries of public and private firms. For example, we collect all subsidiary names of Invitation Homes (e.g., "ih

[20]The price needs to be above the 99th percentile within a county to be identified as "an abnormally high price".
[21]We again anonymize property IDs as well as firm names.
[22]We also tried dividing the bundled price by the number of chunky transactions in each bundle, but the resulting adjusted prices seem quite different from the hedonic-predicted prices.

Table A4: Examples of Chunky Transactions

PropertyID	Price	Buyer	Seller	Date
1	6,120,000	Construction Firm LLC	Firm A LLC	19oct2006
2	6,120,000	Construction FirmLLC	Firm A LLC	19oct2006
3	6,120,000	Construction Firm LLC	Firm A LLC	19oct2006
...	6,120,000	Construction Firm LLC	Firm A LLC	19oct2006
16	6,120,000	Construction Firm LLC	Firm A LLC	19oct2006
17	6,120,000	Construction Firm LLC	Firm A LLC	19oct2006
18	6,120,000	Construction Firm LLC	Firm A LLC	19oct2006
		...		
43	9,275,000	Rental Firm LLC	Holding Company LLC	28jul2006
44	9,275,000	Rental Firm LLC	Holding Company LLC	28jul2006
45	9,275,000	Rental Firm LLC	Holding Company LLC	28jul2006
...	9,275,000	Rental Firm LLC	Holding Company LLC	28jul2006
75	9,275,000	Rental Firm LLC	Holding Company LLC	28jul2006
76	9,275,000	Rental Firm LLC	Holding Company LLC	28jul2006
77	9,275,000	Rental Firm LLC	Holding Company LLC	28jul2006

equity", "ih borrower", etc.) reported by its 10-Ks and use these keywords to identify subsidiaries in CoreLogic data. Similarly, we only use keywords such as "PROGRESS RES" and "PROGRESS R " to identify subsidiaries for Progress Residential, a private company that does not disclose any information about the exact names of its subsidiaries. We complement the 10-K filings and string abbreviation search methods using OpenCorporates and other corporate registration websites to further find subsidiaries for both public and private firms. First, we check which legal entities have purchased large amounts of homes, then we search those names in the corporate registration website looking for evidence of a legal relationship such as shared headquarters, directly reported subsidiaries, etc. Finally, if we are not able to link these often opaque legal names to a more familiar parent company, we search for court cases, legal filings, and news articles that report business relationships. We do this for the top 10,000 largest entities by mean holding, in units.

Table A5: 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 A6: 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 ZORI Sample Discussion

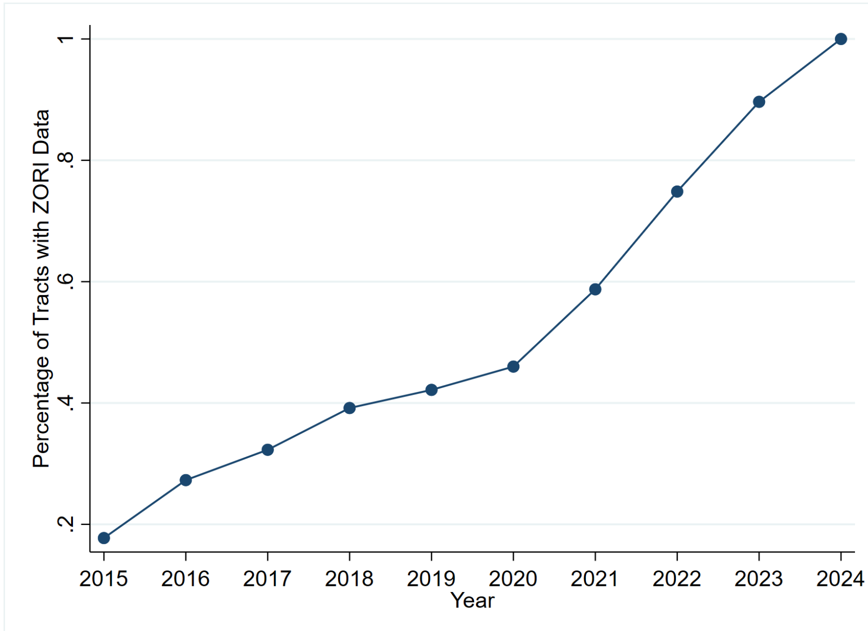
In this section, we test whether Zillow adds ZORI data in a manner correlated with LTR entry. Our main concern is that if the ZORI data generation process follows LTR share, or they share similar drivers, sample selection may bias our rental analysis.

Figure 10 summarizes the ZORI data availability and relationship with LTR share. In panel (A), we plot the share of tracts in our final ZORI sample by the year that the tract entered the sample. To do so, we first create a balanced panel of tracts that ever show up in the ZORI data after it has been crosswalked (the ZORI data is available for zip codes, not tracts). Next, we check whether there is ZORI data available for each year between 2015 and 2022, for each tract. Finally, we plot the share of tracts that exist in each year. As Panel A shows, only 20% of the eventual universe of ZORI tracts existed in 2015, with the fastest growth in new tracts occurring between 2020 and 2024.

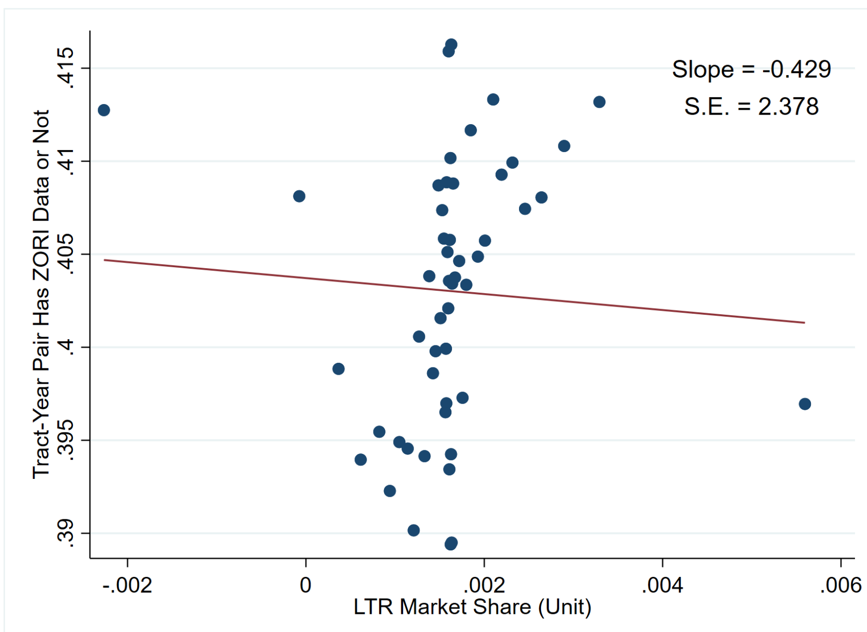
In panel (B), we check to see whether this staggered entry of tracts into the ZORI sample is correlated with LTR market share. To do so, we run a binned scatter plot, controlling for census tract level fixed effects, as well as county time trends. When reporting the regression slope and standard error, we cluster standard errors by county to allow for local correlation across tracts and years. For ease of inspection, we trim the sample for LTR share change outliers. In particular, we flag a tract-year as an outlier if at any point it experienced an annual change in LTR share below the 0.5^{th} percentile or above the 99.5^{th} percentile. We then remove the entire tract from the sample.

Figure 10 Panel B shows there is no meaningful relationship between LTR market share and whether a tract exists in a given year in our ZORI data. The figure shows that over most of the sample, for a given level of LTR market share, there is wide variation in whether a tract-year exists in the sample. We do seem to have outliers in both tails driving the slope, but we cannot statistically distinguish the slope from zero. Finally, the magnitude of the variation explained by LTR market share is economically very small; while the unconditional probability of a tract existing in the data in a given year varies from less than 20% to 100% in Panel (A), LTR share can explain *at most* only 2.5% of the variation (=0.415-0.39) in whether a particular tract-year has ZORI data available. We conclude that the ZORI data expansion is not meaningfully correlated with LTR's market share.

Figure 10: ZORI Data Entry and Correlation with LTR Share



(A) Tracts with ZORI, by Year

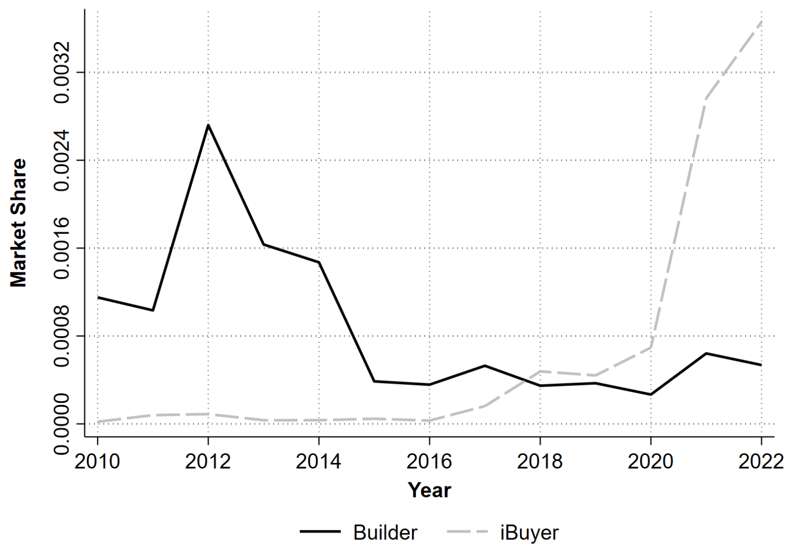


(B) Relationship between ZORI availability and LTR Share (levels)

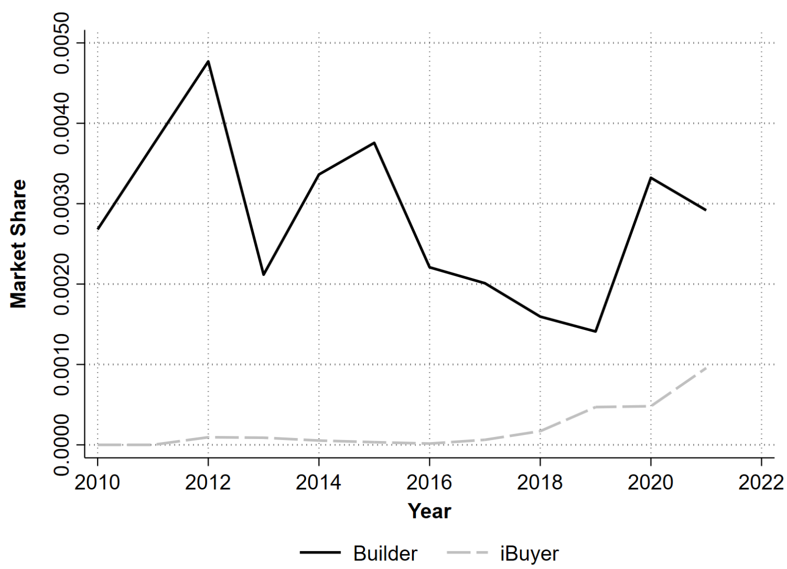
Notes: Panel A plots the availability of tracts in the final rental sample, by year between 2015–2024. We collect all tracts that ever show up in the ZORI data, and plot the share available in each year. Panel B displays the relationship between ZORI availability and LTR share, in levels, pooling over the years 2015–2022, as our LTR share variable ends in 2022. The binscatter controls for tract fixed effects as well as county-level linear time trends, and LTR share is trimmed of outliers at the 0.5^{th} and 99.5^{th} percentiles for ease of inspection. Results are robust to not trimming. Standard errors are clustered at the county level when estimating the slope coefficient and standard error.

C Appendix Figures

Figure C1: Transaction Shares for Builders and iBuyers

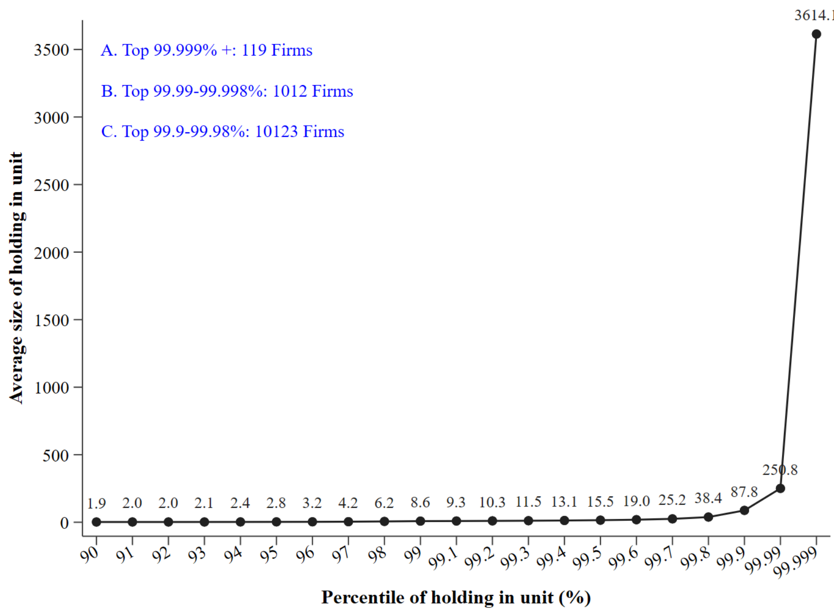


(A) Purchases



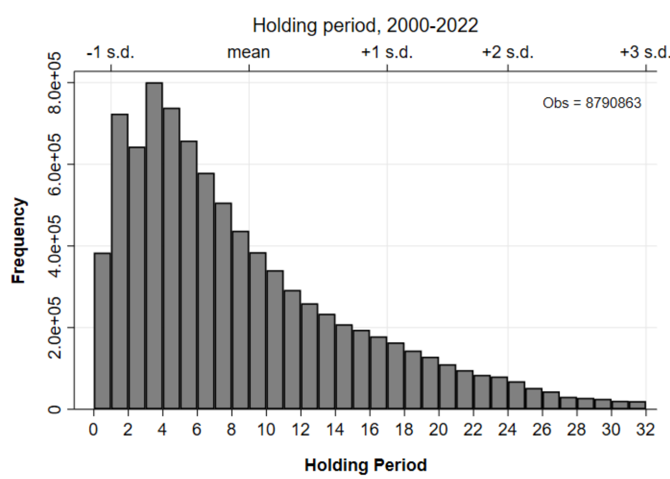
(B) Sales

Figure C2: 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 C3: Distribution of Investors' Mean Holding Periods



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.