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Institutional Investors, Rents, and Neighborhood Change in the Single Family Residential Market

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Abstract

Institutional investors that buy and rent out single family homes have continued to increase their presence after the Great Recession. We examine their neighborhood entry choices and rent charging behavior by leveraging tax and deed transfer records and Multiple Listings Service (MLS) data for 2010-2021. We find that investor share is higher in markets with lower housing values and higher shares of black and non-college residents, but higher median income. We also find that investors raise rents at 60% higher rates than the average increase when first acquiring the property, and higher investor share in a neighborhood is correlated with faster rent increases for non-investor landlords. We do not find evidence that investor entry is associated with gentrification, as neighborhoods with high investor activity saw reductions in White and college educated resident share relative to other neighborhoods in their metro area.

Keywords: real estate, institutional investors, single family residential market, rentals

JEL Classifications: G23, R21, R23, R31

1 Introduction

A new class of residential arrangement has emerged following the foreclosure crisis: single-family residence (SFR) rentals that are owned, operated, and managed by large financial firms. These are typically funded by a new class of bonds called Rent-Backed Securities (RBS) that take rents collected from a geographically diversified set of SFR rentals to make

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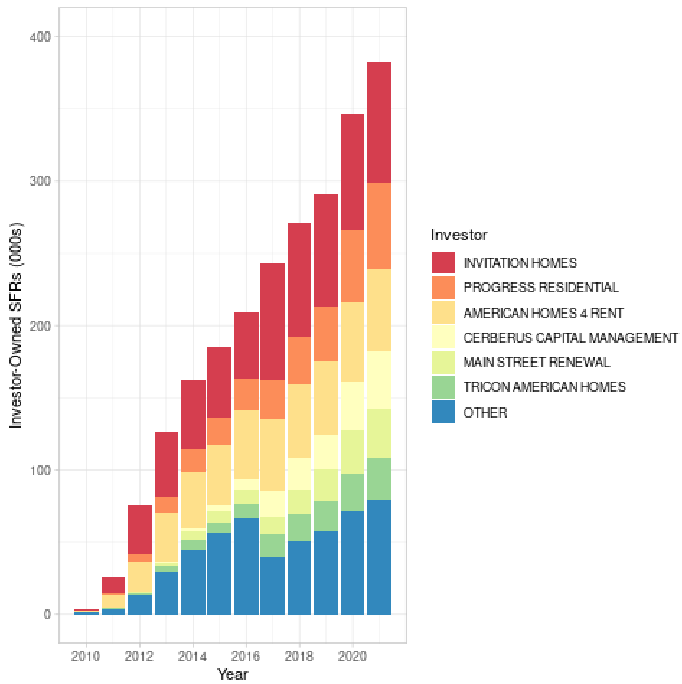
Figure 1. Trends in Institutional Investor Ownership Over Time



Note: This figure plots count of investor-owned SFRs in thousands by investor name and year, 2010-2021. Investors are identified using names and mailing addresses of owners (in tax records) or buyers (in deed transfer records), in conjunction. Source: Authors' calculation from CoreLogic Tax and Deeds Data.

coupon payments to investors. From holding almost no properties around 2010, these firms acquired almost 400,000 properties by 2021 (Figure 1).[1]

This relatively new phenomenon has attracted scrutiny from both academics and policymakers. Starting with Mills et al. (2019), papers have examined the effect of buy-to-rent investor entry into the housing market. Policymakers, meanwhile, have been cautious of the rise of investor-owned rentals. For example, the United Nations has called it "financialization of housing."[2] The United States Congress has proposed a bill to force the sale of housing owned by hedge funds and various Wall Street institutions and ban any future ownership.[3]

[1]Most recently (2023), their pace of acquisitions has slowed down, but they are still acquiring a significant number of properties. See "For Property Investors, the Price of Homes Is Still Not Right", *Wall Street Journal*, https://www.wsj.com/real-estate/for-property-investors-the-price-of-homes-is-still-not-right-e6ab67c8.

[2]Letter OL OTH 17/2019 from the UN Office of the High Commissioner for Human Rights on the issue of Housing Financialization.

[3]"New Legislation Proposes to Take Wall Street Out of the Housing Market," *New York Times*, https://www.nytimes.com/2023/12/06/realestate/wall-street-housing-market.html.

However, little is known about the most recent trends in entry characteristics of investors in the SFR market as well as their rent-charging behavior on the properties they own. While previous studies have focused on a particular geography, usually one or two Metropolitan Statistical Areas (MSAs), or the impact on neighborhood-level rents, to our knowledge, no study has explored how investors set rents differently from non-investors.

In this paper, we directly examine the rent-charging behavior and neighborhood effects of investor-owned SFR rentals on a national scale. To do so, we mainly use two sources of data: 1) property deed transfer records and tax assessment data from county recorder's and assessor's offices and 2) Multiple Listing Service (MLS) data across the nation,[4] both aggregated by CoreLogic. We use the tax and deeds data to identify owners of properties and merge with MLS data to compare the rental listings of investor- and non-investor-owned properties and merge with Census data to examine neighborhood characteristics of places with high versus low investor activity. In particular, national-level MLS data is a new source of data that allows us to directly observe the rent-charging behavior of properties owned and operated by Wall Street investors. Unlike previous studies, we have the advantage of being able to move beyond a handful of geographies.

We start by documenting various facts about investor activity during 2010-2021. We find that, while large variations across neighborhoods and cities exist, investors generally increased their holdings in markets where they already had presence during 2010-2015. In addition, while distressed sales were a major source of acquisition in the very early periods, by 2015, more than 70% of their acquisitions were non-distressed sales. We also extend the work of Mills et al. (2019) to explore the characteristics of neighborhoods (Census tracts) that have experienced large increases in investor share of SFRs. Using ordinary least squares (OLS), we explore how the patterns that they observe from 2010 to 2015 differ from our extended sample period. We find that investors pursued their strategy to expand their presence in neighborhoods with higher minority share, lower college educated share, and

[4]MLS collectively refers to platforms where real estate agents post sale and rental listings, typically operated by local real estate boards.

higher homeowner share more intensely from 2010 to 2020 than from 2010 to 2015.

Next, we explore investors' rent-charging behavior by comparing rents of investor-owned properties to non-investor properties in the same neighborhood listed in the same quarter. We utilize both a cross-sectional OLS specification and a repeat-rent specification to deal with any selection bias arising from unobserved static property characteristics. We show that investors significantly raised rents when first turning over the property, at 60% higher than the average rate, but followed up with more modest, albeit higher, rates of increase thereafter of about 7% above the average rate. Meanwhile, we find evidence that investors pushed up rents of nearby properties. To see if various explanations can account for this more aggressive rent behavior, we explore several mechanisms that could contribute to such a heightened pace of increases in rents compared to non-investor-owned properties. While investor-owned properties do seem to engage in higher renovation activity, our results of high rent increases hold even after controlling for our measure of renovations. Moreover, we do not find evidence that renovations done by investors result in higher rent increases.

We find suggestive evidence that investors turn over their properties at a higher rate, perhaps allowing them to be more aggressive in extracting market rents from their properties than non-investors. We also find evidence that market power matters, similar to results of Gurun et al. (2022), as a higher share of SFRs available for rentals decreases investors' ability to raise rents more aggressively.

Finally, we explore the effect of investors on neighborhood change beyond rents. We first explore the change in various neighborhood characteristics, including through a composite Socioeconomic Status (SES) measure developed in Baum-Snow and Hartley (2020), which computes the relative standing of the neighborhood's White share, college-graduate share, and median household income compared to the CBSA average. We also explore changes among mortgage borrowers using the Home Mortgage Disclosure Act (HMDA) data for both new purchases and refinances in order to investigate potential differences in patterns among "movers" and "stayers" in high investor neighborhoods. Altogether, we see evidence that the White and college graduate population shares have decreased for high investor share neighborhoods. This suggests that neighborhoods with high investor entry do not seem to gentrify following their entry.

Overall, our findings suggest that investors enter into neighborhoods with higher minority shares but lower housing values, raise rents at faster paces, and the neighborhoods that they enter do not seem to undergo gentrification at higher rates than others. This paints a nuanced picture of their role in the housing market that requires a more careful view on implications for policy.

1.1 Existing Literature

The direct evidence of investors and their impact on rent has been limited. Most studies have focused on rent indexes and not on property-level rents charged by the owners. Few studies focusing on property-level rents have only explored a small geographic area, especially focusing on markets with a lot of activity (typically Atlanta).

Still, buy-to-rent and "Wall Street" investors have been a focus of an active literature. To our knowledge, Mills et al. (2019) was the first paper to systematically study large buy-to-rent investors. While their paper was broader in scope, exploring investors of all sizes (from "micro" investors purchasing 1-2 units per year to buy-to-rent investors), they explored characteristics of neighborhoods into which they entered as well as a few outcomes, such as neighborhood-level prices and unemployment.

The most comprehensive study of buy-to-rent investors' impact on rents and neighborhoods is Gurun et al. (2022). They exploit mergers as a potential source of exogenous variation to explore the effects of expansion of investor activity on neighborhood- and property-level rents. In particular, they compare neighborhoods where two merging firms have a large overlapping presence against neighborhoods where they do not overlap. They find that rents increase, but so does the "quality" of neighborhoods as measured by the hiring of security guards, streetlight density, and other outcomes. Our study differs from theirs mostly in geographic breadth at the sacrifice of causal identification. They also focus on one mechanism of market share (defined by the number of SFRs owned by a single investor entity in a neighborhood), which only affects a relatively small share of neighborhoods with investor presence.

Other papers have looked at the effect of large-scale investors on neighborhood change. Austin (2022) uses mergers to show that, following increases in investor concentration in a neighborhood, price and rent indices rise, but there is also increased diversity as evidenced by mortgage applications and originations of minorities. Raymond et al. (2018) explores eviction rates and finds that large institutional investors are more likely than other landlords of single-family rental housing to file for eviction. Raymond et al. (2021) focuses on investor purchases of multi-family units, and finds that they are followed by an increase in evictions and a gain in White population share at the expense of Black population share. Importantly, all three studies only focus on Atlanta.

A few papers have focused on various kinds of investors' entry into the property market, especially following the Great Recession (see, e.g., Lambie-Hanson et al. (2022), Ganduri et al. (2023)). While they do not focus specifically on buy-to-rent investors, they also provide insight into patterns of entry and effect on house prices similar to what we observe in the data.

Overall, our contribution to the literature is threefold. First, we explore the behavior of buy-to-rent investors more comprehensively in terms of geography and time periods covered. Second, we directly examine the rent-charging behavior of investors. Finally, we explore a set of neighborhood characteristics separately for different groups on a set of outcomes focusing on gentrification.

The rest of the paper proceeds as follows: in Section 2, we explain in more detail who the investors we focus on are, our methodology to identify them in the data, and stylized facts pertaining to their entry into neighborhoods. Section 3 explores how rent-charging behavior differ between investors and non-investors using the MLS data. In Section 4 we explore how neighborhood characteristics have changed following investor entry. We conclude in Section 5.

2 Who Are Institutional Investors?

The term *institutional investors* can refer to many classes of investors in the housing market. In this paper, we focus on a subset of *buy-to-rent* investors that are known as "Wall Street" investors. These firms are usually subsidiaries of large Wall Street private equity firms and issue rent-backed securities to fund their purchases of single-family residences for the purposes of renting. Unlike traditional investors, buy-to-rent investors are primarily focused on generating income from renting out SFR properties instead of holding them for resale.

One prominent example is Invitation Homes, a publicly traded company that is a subsidiary of Blackstone Inc. Invitation Homes received media attention as one of the early actors in the space and one of the first to offer rent-backed securities as an asset class. Rent-backed securities (RBS) are usually pass-through securities, taking rent payments collected from a predetermined portfolio of SFR rentals to make payments to bondholders. In this sense, they are akin to mortgage-backed securities in the residential real estate market or lease-backed securities in the commercial real estate market.

2.1 Data and Identifying Investors

Like previous studies (e.g., Mills et al. (2019), Lambie-Hanson et al. (2022)) we utilize tax assessment and deed transfer records aggregated by CoreLogic. Tax assessment data includes properties' physical characteristics (such as number of bedrooms) and ownership information (such as the names of the owners and associated mailing addresses). These data are collected by individual counties' tax assessors offices for the purposes of generating assessed valuations to collect tax bills from owners. Deed transfer records contain information on sales and mortgages on the properties, with names of sellers and buyers in cases of transfer deeds and lenders and borrowers in cases of mortgage deeds. These data are collected by individual counties' recorder's offices for the purposes of tracking ownership of parcels and properties in the county.[5]

We identify the buy-to-rent institutional investors by using an owner's address information in the tax assessment and/or a buyer's address information in the deed transfer records. Using these addresses, we identify a potential ownership entity. Then, for all properties sharing the same address, we look through the buyer/owner names. While we use the name information, we elect to use addresses as the primary source of identification rather than names due to the large variation in names associated with these types of investors.[6,7,8] As a final part of our identification process, we use string matching on a strict set of owner's names to supplement our identified investors.[9]

2.2 Patterns of Investor Entry

In this section, we describe the patterns of investor entry we see in the data from 2010 to 2021. In particular, we present the following stylized facts:

1. Investors continued to increase their holdings from 2010 to present
2. While still a small share of the overall U.S. market, some markets (metropolitan areas) have a relatively high share of investors
3. Even within markets, there is a large variation in investor presence across neighborhoods

[5]The CoreLogic Tax and Deeds data increases the number of counties it covers over time. However, the time trend of investor-held SFRs shown in Figure 1 looks very similar if restricted to counties covered by CoreLogic in 2010.

[6]This is because often a new special purpose vehicle (SPV) is created to hold properties that will enter into an RBS deal. While these SPVs have different names, they usually share addresses.

[7]There are a few addresses that can be tied to large business complexes or address companies that provide services to receive correspondences for other businesses. We identify these kinds of addresses using the associated owner/buyer names and exclude them.

[8]Note that this identifies certain investors that transfer management rights to these companies. For our purposes, as long as these management rights include pricing rights, they can be treated as functionally equivalent.

[9]We compare our counts with Amherst Capital's publications and find that they are mostly similar but over-counting a few investors' totals (See Table A1). A major source of difference is the fact that we include properties not owned but managed by investors.

Table 1. Top 15 CBSAs By Share of Investor SFR Ownership

Rank	CBSA	% Investor
1	Atlanta-Sandy Springs-Alpharetta, GA	3.03%
2	Jacksonville, FL	2.97%
3	Charlotte-Concord-Gastonia, NC-SC	2.65%
4	Tampa-St. Petersburg-Clearwater, FL	2.18%
5	Memphis, TN-MS-AR	2.17%
6	Indianapolis-Carmel-Anderson, IN	2.15%
7	Orlando-Kissimmee-Sanford, FL	2.06%
8	Phoenix-Mesa-Chandler, AZ	1.94%
9	Las Vegas-Henderson-Paradise, NV	1.82%
10	Nashville-Davidson–Murfreesboro–Franklin, TN	1.80%
11	Lakeland-Winter Haven, FL	1.69%
12	Raleigh-Cary, NC	1.66%
13	Columbia, SC	1.48%
14	North Port-Sarasota-Bradenton, FL	1.37%
15	Birmingham-Hoover, AL	1.28%

Notes: This table lists 15 Core-Based Statistical Areas (CBSAs) with the highest shares of investor-owned single family residences (SFRs). Shares of investor-owned SFRs are calculated as count of investor-owned properties divided by count of SFR properties in the tax records. We use the SFR definition from CoreLogic's standardization of land use descriptions from states and counties. Source: Authors' calculation from CoreLogic Tax and Deed records.

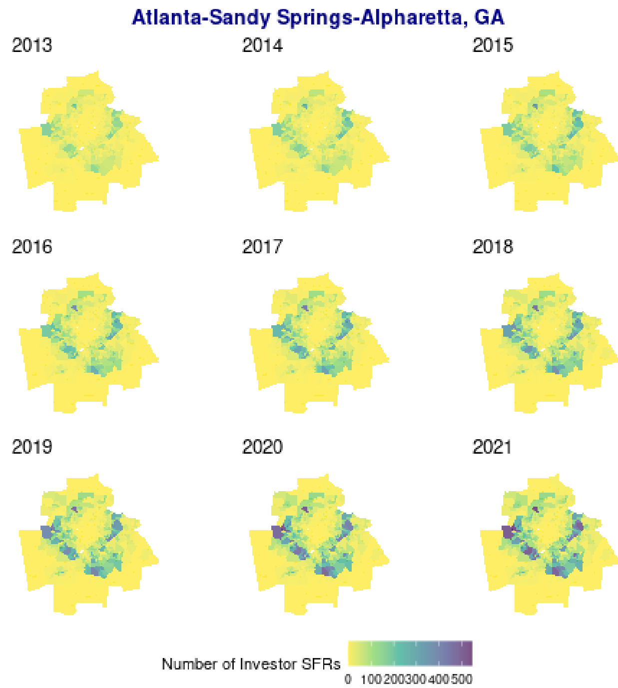
4. About 65% of increase in investor presence in recent periods is on the intensive margin rather than entry into new neighborhoods

5. The source of acquisitions has moved away from foreclosures since 2016

As shown in Figure 1, investors ramped up their holdings from 2010-2021. The pace of acquisitions never slowed down, even accelerating during the pandemic. Total holdings rose to around 400,000 by the end of our sample period in 2021. Moreover, unlike other types of investors, the institutional buy-to-rent investors we focus on typically hold on to their acquisitions, consistent with their business model.

Investor-owned SFRs are a small share of the overall SFR market. However, in some Core-Based Statistical Areas (CBSAs), the share of investor-owned properties is more significant. In Table 1, we list the top 15 CBSAs by investor ownership share. The Atlanta metro area has the largest share of investors at 3% of its SFR stock. We also see other metro areas that have significant shares – these include the Charlotte metro area (2.65%) and large cities in

Figure 2. Share of Investors in Census Tracts of Atlanta CBSA



Notes: This figure plots Census tracts of Atlanta-Sandy Springs-Alpharetta Core-Based Statistical Area (CBSA) by the number of investor-owned Single Family Residences (SFRs). We use the SFR definition from CoreLogic's standardization of land use descriptions from states and counties. Source: Authors' calculation from CoreLogic Tax and Deed records.

Florida, like Jacksonville, which is just under 3% of SFRs.

Even within markets, there is a large variation in the share of investor ownership across neighborhoods. In Figure 2 we plot the share of investors across census tracts in the Atlanta CBSA. We see the number of investor-owned properties is not evenly distributed across the city, with high concentration particularly surrounding downtown Atlanta and in areas with high minority populations.

We also explore whether investor entry across time periods is coming from entry into new neighborhoods and markets ("extensive margin") or a higher concentration within neighborhoods and markets where they are already present ("intensive margin"). To do so, we split the sample period in two, 2010-2015 and 2015-2020, and examine whether a Census block group or tract experienced any increase in investor share, and if so, whether there was

Table 2. Increases in Holdings in Recent Periods Driven by the Intensive Margin

Panel A: Block Group

Year	No Increase	Entry	Intensive	Total #
2010-2015	85.47%	14.08%	0.45%	198,975
2015-2020	87.39%	5.25%	7.36%	210,677
Total	86.46%	9.54%	4.01%	409,652

Panel B: Tract

Year	No Increase	Entry	Intensive	Total #
2010-2015	76.82%	21.99%	1.19%	67,943
2015-2020	79.78%	6.97%	13.24%	71,363
Total	78.34%	14.30%	7.36%	139,306

Notes: Displays percent of Block Groups (Panel A) or Tracts (Panel B) that experienced either no increase in investor share, the entry of investors (from 0% to positive percent), or an increase in the intensive margin (from >0% to increase) between 2010-2015 and 2015-2020. Total # refers to number of Block Groups or Tracts in the sample. Source: Authors' Calculation from CoreLogic Tax and Deed records.

investor presence in the previous period.

Table 2 shows the breakdown of block groups (Panel A) and tracts (Panel B) with no increase in investors, an increase of investors from entry, and an increase of investors in the intensive margin for 2010-2015 and 2015-2020. For 2010-2015, by virtue of investor activity starting around 2012, most of the increase in investor presence came from entry. However, for 2015-2020, around two-thirds of the increase in investor presence came from the intensive margin rather than entry. This is more pronounced when looking at larger geographic units (tracts) compared to smaller units (block groups), but the patterns are similar.

Moreover, the source of acquisition for investors have changed over time. Table 3 breaks down the source of acquisition into foreclosure, real estate owned (REO), short sale, and non-distressed sales. From 2010 to 2012, the majority of acquisitions came from distressed sales. Even through 2016, distressed sales accounted for 20% of investor purchases. However, starting in 2017, less than 10% of acquisitions came from distressed sales with almost none coming from distressed sale by 2018.

Finally, we extend the work of Mills et al. (2019) to examine the factors correlated with the entry of investors into particular Census tracts. We utilize tract-level ordinary least

Table 3. Source of Investor Acquisition by Year

	Distressed			Non-	Total #
Sale Year	Foreclosure	REO	Short Sale	distressed	(Thousands)
2011	0.31	0.29	0.08	0.32	1
2012	0.44	0.11	0.09	0.36	26
2013	0.27	0.09	0.11	0.53	60
2014	0.22	0.09	0.06	0.62	49
2015	0.16	0.08	0.04	0.72	33
2016	0.12	0.05	0.04	0.80	23
2017	0.05	0.02	0.01	0.92	33
2018	0.02	0.01	0.00	0.96	38
2019	0.01	0.01	0.00	0.97	32
2020	0.00	0.02	0.00	0.98	25
2021	0.00	0.00	0.00	0.99	77

Notes: This table breaks down new investor purchases by their source into the following categories: foreclosure, real estate owned (REO), short sale, or non-distressed. We use CoreLogic-derived categorization of distressed sale, which looks at the type of deed filed and entity and types of sellers. Source: Authors' calculation from CoreLogic Tax and Deed Records.

squares (OLS) specification to examine conditional correlations between investor share and various baseline tract characteristics in 2010. Specifically, we use the following specification:

$$PctInvestor_{nct} = \beta X_{nc,2010} + \gamma_c + \varepsilon_{nct}, \tag{1}$$

where $PctInvestor_{nct}$ is the percent of investor-owned SFRs in tract n belonging to county c in time $t \in (2015, 2020)$, $X_{nc,2010}$ is a vector of tract characteristics in 2010 from the American Community Survey (ACS) 2006-2010 Summary File, and γ_c are county fixed effects.

Table 4 presents our results from the entry specification, equation (1). Column (1) shows that the investor share in 2015 was greater in tracts with lower home values, higher Black population shares, lower college graduate population shares, and higher homeownership shares. While investors were entering lower housing value areas, they do not appear to have targeted the poorest or most dilapidated neighborhoods. Larger investor shares were associated with higher household incomes as well as a younger housing stock and population. These results are largely consistent with the findings in Mills et al. (2019), which examined the 2012-2014 time period.

Table 4. Investor Entry Tract Characteristics

	Dep Var: Investor SFR Percentage	
	2015 Inv Pct	*2020 Inv Pct*
Log Median Household Income	0.0930***	0.191***
	(0.0271)	(0.0442)
Log Zillow Home Value Index	-0.0763**	-0.0990**
	(0.0385)	(0.0489)
Percent Black	0.00244***	0.00551***
	(0.000661)	(0.00108)
Percent Non-White Hispanic	0.000675	0.000523
	(0.000762)	(0.00119)
Percent Asian	-0.00105	-0.000745
	(0.000665)	(0.000951)
Percent College Graduate	-0.00394***	-0.00810***
	(0.000640)	(0.00132)
Median Age	-0.0141***	-0.0242***
	(0.00162)	(0.00289)
Percent Homeowned	0.00262***	0.00543***
	(0.000468)	(0.000896)
Percent SFR Rentals	-0.000038	0.000178
	(0.000518)	(0.000722)
Percent Vacant Housing Units	-0.00123**	-0.00186**
	(0.000599)	(0.000945)
Percent Housing Units Built After 2000	0.00662***	0.00900***
	(0.000887)	(0.00140)
Percent Housing Units Built Prior to 1950	-0.00146***	-0.00277***
	(0.000386)	(0.000631)
Average Household Size	-0.0513**	-0.156***
	(0.0199)	(0.0329)
Percent Families Married	0.00157***	0.00200**
	(0.000486)	(0.000838)
Log Population	0.0505***	0.105***
	(0.0120)	(0.0191)
County Fixed Effects	YES	YES
N	55,768	55,768
R-squared	0.356	0.372

Notes: This table shows Ordinary Least Squares (OLS) regression results from equation 1. Standard errors clustered on county shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Tracts not in a Core-Based Statistical Area (CBSA) or that are in a CBSA with no investor presence by 2021 are excluded. Data Source: Tract characteristics sourced from the Census Bureau's American Community Survey 2010 5-year summary file, Zillow Home Value Index (ZHVI) from Zillow, and investor percentage from authors' calculation based on CoreLogic Tax and Deeds Data. ZHVI is converted to tract-level using the U.S. Department of Housing and Urban Development (HUD) 2020Q3 zip code to tract correspondence.

In Column (2) we extend the analysis using the 2020 investor share as the outcome variable in the regression. We continue to use 2010 tract characteristics as the covariates. The results are identical in direction to the 2015 results, but the coefficients tend to be larger in magnitude. This is not surprising given our finding that the majority of the increase in investor-owned SFRs during the 2016-2020 period was on the intensive margin. It also provides suggestive evidence that, compared to the earlier period, investors intensified their efforts in tracts with these characteristics during the 2016-2020 period.

3 Rent-Charging Behavior of Investors

In this section, we directly examine the rent-charging behavior of investors by using a new source of data collected from local MLS Boards by CoreLogic. We first describe our data, then our analytic framework, and finally present our rent results.

3.1 Data

Our main source of data for rent analysis is the CoreLogic MLS data. CoreLogic aggregates local MLS Board's sale and rental listings from around the country. MLS data contains agent-input information on property characteristics (such as number of bedrooms, number of bathrooms, the size of the property, etc.) and listing history (such as the number of days on market and price changes in the form of maximum and minimum of the listing price throughout the life of the listing). Moreover, we also have agent comments on the property that we exploit to extract renovation information. We only use closed rental listings (i.e., properties that have been rented), which have information on the contract rent that allows us to observe the exact rent that is being charged, not just the asking rent.[10]

Using this data, we explore two specifications to investigate how investors differ in their

[10] While this circumvents problems from other rental data that only has asking or survey-based rent, we still miss any concessions or deals that are not reflected in the price of the rent, such as whether utilities are included.

rent-charging behavior from non-investors, which we detail in the next section.

3.2 Cross-Sectional and Repeat-Rent Specification

For a property i listed for rent at time t in neighborhood n, we can think of a rent model:

$$\log(Rent_{int}) = \beta Investor_{it} + \gamma_i + \gamma_{it} + \gamma_{nt} + \varepsilon_{int}, \tag{2}$$

where $Investor_{it} \in (0, 1)$ is the investor status of property, γ_i, γ_{it}, γ_{nt} are vectors of static house characteristics, dynamic house characteristics, and year-quarter-neighborhood characteristics, respectively, and ε_{int} are idiosyncratic property-time-neighborhood characteristics.

The central identification challenge comes from the fact that we cannot observe all relevant static and dynamic housing or neighborhood-time characteristics. The OLS estimate on β will be biased to the extent that any unobserved characteristics are correlated with investors' decision to purchase and rent the property and/or their strategic rent-setting behavior. In order to deal with this, we take two main approaches. First, we include as many sets of observable property characteristics as feasible and neighborhood-time fixed effects. Second, we utilize a repeat-rent specification.

In our first approach, we include a vector of housing characteristics to proxy for γ_i and γ_{it} and include neighborhood-time fixed effects to address γ_{nt}. For static housing characteristics, we include log area, number of bedrooms fixed effects, number of bathrooms fixed effects, an indicator for having a garage, and decade built.[11] For dynamic characteristics, we include the log of assessed valuation from the tax roll at the time of the listing. For listing characteristics, we include the log of Days on Market (DOM) to control for any factors that may have affected the listing that we can capture from the length of availability of the listing. Finally, for neighborhood-time fixed effects, we successively control for county-year-quarter

[11] For number of bedrooms and number of bathrooms, we include a fixed effect for every integer value until 10 rooms, where we group observations with 10 or more rooms into the same category. For the garage indicator, we have three values: having a garage, not having one, and no information. For decade built, we combine the actual year built and effective year built, taking the effective year built if it exists.

(County-YQ, e.g., Philadelphia County in 2020Q1), Census tract-year-quarter (Tract-YQ), and Census block group-year-quarter (BG-YQ). We do this to assess the effect of geography on investor rent-charging behavior, informed by our earlier findings that there is considerable heterogeneity of investor activity in different geographical granularity.

In our second approach. we use a repeat-rent specification. First-differencing equation (2), yields the following specification:

$$\Delta \log(Rent_{int}) = \sum_{j} \beta_j * I(\Delta Investor_{it} = j) + \Delta\gamma_{it} + \Delta\gamma_{nt} + \Delta\varepsilon_{int}, \tag{3}$$

where $\Delta Investor_{it}$ is change in investor status between listings,

$$\Delta Investor_{it} = \begin{cases} 1 \text{ if } Investor_{int} = 0, Investor_{int-1} = 0 \\ 2 \text{ if } Investor_{int} = 1, Investor_{int-1} = 0 \\ 3 \text{ if } Investor_{int} = 0, Investor_{int-1} = 1 \\ 4 \text{ if } Investor_{int} = 1, Investor_{int-1} = 1. \end{cases} \tag{4}$$

$\Delta\gamma_{it}$ is changes in dynamic home characteristics, $\Delta\gamma_{nt}$ is changes in neighborhood characteristics, and $\Delta\varepsilon_{int}$ is change in property-neighborhood-time-level characteristics.

This specification can effectively deal with any omitted variable bias arising from unobserved static property characteristics.[12] Remaining endogeneity comes from unobservable changes in dynamic home characteristics and neighborhood characteristics, $\Delta\gamma_{it}$, $\Delta\gamma_{it}$, respectively. Note that both dynamic home and neighborhood-time characteristics include not only actual changes in characteristics that we do not observe but also static characteristics for which valuations change over time. For example, quality changes from renovations would be the former case while changes in renters' valuation for the number of bedrooms would be

[12]Compared to a simple property FE specification, we prefer using the repeat-rent specification to explicitly estimate the changes in rent under different scenarios of ownership change. As shown by Bayer et al. (2017), property FE specification with an investor indicator (the minority indicator in their case) would identify a single β off of changes in investor status over time, but would not be able to distinguish the effect of changes from investor to non-investor or vice versa.

the latter. Both kinds of unobservable changes can still bias our estimates in the repeat-rent specification.

To deal with endogeneity arising from changes in home characteristics, we take the following approaches. As before, we proxy for dynamic characteristics by changes in home assessment value and listing days on market. Changes in the home's assessment value, to the extent that it takes into account market value, will capture some of the changes in dynamic characteristics or valuations that we do not observe. Changes in the listing days on market might also capture this—for example, the same property listed before and after quality updating should see a decrease in the listing days on market.

Another approach we use is to include our measure of renovations from the agent-input "Public Remarks" in the MLS data. The Public Remarks section includes any additional qualitative and quantitative information the agents write in order to communicate non-standardized characteristics in their listings. These often include descriptions of the property that go beyond just standard hedonic characteristics. We tag a listing as renovated if public remarks contain the following string values anywhere: "newly, renovated, renewed, updated, rehabbed, remodeled." We make sure to exclude "new construction, newly constructed" in order to avoid capturing new construction. This allows us to capture any potential quality changes in the home that we cannot observe from other sources of data, such as county records.

Finally, in order to deal with dynamic neighborhood characteristics, $\Delta\gamma_{nt}$, we take two approaches. First, we use a simplified proxy by including neighborhood-time fixed effects at the time of listing t, γ_{nt}, and number of years between current and previous listing that is being used in the repeat-rent observation, $\Delta Year_t$. This supposes that from a certain time, neighborhood changes occur linearly in the number of calendar years between the listings.[13] Second, we take a more stringent approach and include two sets of fixed effects, $\gamma_{nt}, \gamma_{nt-1}$. This specification essentially compares properties listed within the same neighborhood at

[13] This also captures any potential changes in property characteristics, to the extent that listings further apart are more likely to have experienced quality changes (either negative or positive) over time.

Table 5. Summary Statistics for MLS Data

Sample:	Cross-Section		Repeat-Rent	
	Observations	Mean	Observations	Mean
Listed Rent	4468061	2398.56	1269936	1971.99
Contract Rent	3542682	2367.77	1053255	1883.51
Investor Flag	4522308	0.06	1269936	0.08
Corporate Flag	4522308	0.11	1269936	0.12
Living Area (sqft)	4469992	1922.88	1265546	1974.18
Days On Market	4521746	88.27	1269936	58.08
Bedrooms (#)	4522308	3.37	1269936	3.43
Bathrooms (#)	4522308	2.27	1269936	2.37
Garage N	4522308	0.07	1269936	0.05
Garage Data Missing	4522308	0.20	1269936	0.14
Year Built	4460789	1976.72	1263081	1985.44
Assessed Value (County)	4483250	194947.66	1269936	194285.26
List Year	4522308	2014.77	1269936	2016.41
Renovated	4522308	0.12	1269936	0.09

Notes: This table shows summary statistics for our two analytical samples. Cross-Section column shows counts and means for a subset of variables used in our cross-sectional sample. Repeat-Rent column shows them for our repeat-rent sample, which imposes a restriction that properties are listed at least twice. Source: Authors' calculations from CoreLogic MLS Data.

time t and at time $t-1$. This will cut down our sample significantly, but would further control for any neighborhood change over time.

We present summary statistics on the MLS data for our cross-section and repeat-rent samples in Table 5. As expected, the repeat-rent sample is significantly smaller. We see some differences in the two samples, namely that the average listed and contract rents are lower. However, other characteristics are similar in both the cross-section and repeat-rent samples.

3.3 Results

In Table 6, we present the results on our cross-sectional regression specification (2). We use two different rent measures (listed rent and contract rent) and regress them on an indicator variable that equals one if the owner of the property is an investor and zero otherwise. While our focus is on the investor indicator variable, we also include an indicator that equals one if the owner of the property is a corporate investor (but not an institutional investor) and zero otherwise[14] as well as other property characteristics described in Section 3.2. In Panel A, we present the coefficient estimate on the investor indicator on original listed rent and in Panel B, we present results on contract rent, or the final closing rent of the listing. The two can differ due to market forces and negotiations but the results are very similar.

In both panels, going from columns (1) to (4), we include a set of more geographically granular neighborhood-time fixed effects. In the first column, we include no fixed effects. In columns (2)-(4), we include fixed effects generated from year-quarter of listing interacted with county, tract, or block group, respectively. We first observe that when controlling for no set of fixed effects (column 1) or county-year-quarter fixed effects (column 2), investors seem to charge lower rent than non-investors or smaller corporate owners. In Panel A column 2, investors list for around 3.6 percent less. However, as we move down the columns, we see that the differences fade and investors list for around the same amount as others. The results are similar for contract rent.

We interpret these results as demonstrating that investors are likely to hold properties in the lower value markets, not in the highest value markets/neighborhoods. They are in line with our investor entry regressions in Table 4, where we show that investors are likely to enter tracts with lower home values. Interestingly, other corporate owners do not display such a pattern, suggesting that these buy-to-rent institutional investors indeed have a different strategy than other investors and corporate owners.

As stated in Section 3.2, these results are only suggestive of investors' rent-charging behavior due to various unobserved property characteristics. We now turn to our repeat-rent specification, (3).

We present a simple national repeat-rent growth trend in Figure 3 separately for investor-owned and non-investor-owned properties, where the rent is normalized to the 2020Q1 levels

[14] We define corporate owners as those with names containing "LLC", "INC", "CORP", "HOMES" or ownership structure in the form of associations, corporations, or joint ventures as reported to the taxing authority. Since these can capture investors, we let investor and corporate flags be mutually exclusive by setting corporate flags to zero if we identify them as investors.

Table 6. Cross-Sectional Results on Rent Patterns

	(1)	(2)	(3)	(4)
Panel A: Log Listed Rent				
	Log(Listed Rent)			
Investor Flag	-0.0356**	-0.0452***	-0.00167	0.000761
	(0.0161)	(0.00843)	(0.00540)	(0.00523)
Corporate Flag	0.0190	0.00294	-0.00440**	-0.00445**
	(0.0129)	(0.00428)	(0.00184)	(0.00175)
Observations	3,330,505	3,330,499	3,330,505	3,330,505
R-squared	0.369	0.664	0.835	0.860
Avg Rent	2193.226	2193.227	2193.226	2193.226
FE	N	County-YQ	Tract-YQ	BG-YQ

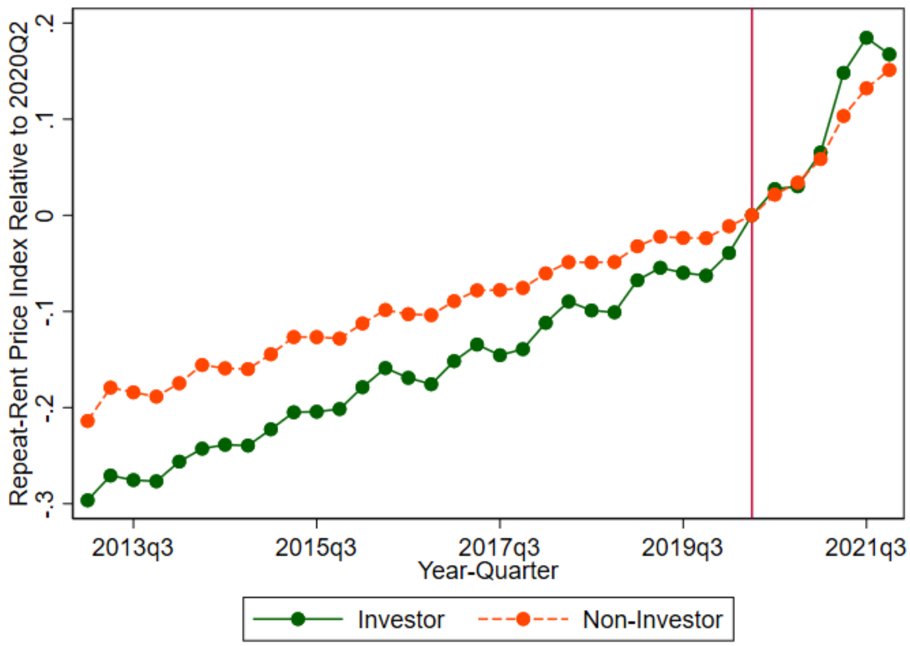
	(1)	(2)	(3)	(4)
Panel B: Log Contract Rent				
	Log(Contract Rent)			
Investor Flag	-0.0331**	-0.0397***	0.00426	0.00641
	(0.0157)	(0.00879)	(0.00527)	(0.00514)
Corporate Flag	0.0134	0.000699	-0.00453***	-0.00440***
	(0.0113)	(0.00387)	(0.00162)	(0.00164)
Observations	2,541,453	2,541,447	2,541,453	2,541,453
R-squared	0.342	0.662	0.846	0.869
Avg Rent	2131.694	2131.695	2131.694	2131.694
FE	N	County-YQ	Tract-YQ	BG-YQ

Notes: Standard errors clustered at the county-level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The Corporate Flag is defined as those with names containing "LLC", "INC", "CORP", "HOMES" or ownership structure in the form of associations, corporations, or joint ventures as reported to the taxing authority. Investor and Corporate Flags are made mutually exclusive by setting Corporate Flag to zero if we identify them as investors. Not shown are various property and listings characteristics described in Section 3. Data Source: CoreLogic MLS, Tax, and Deeds Data.

for the respective property classes. The national-level growth trends already show a faster growth trend in rents from 2013-2020 for investors (around 30% growth) compared to non-investors (around 20%).

In Table 7, we present the results from our repeat-rent specification, where we regress contract rent on two indicators of investor ownership status and various proxies for dynamic

Figure 3. Repeat-Rent Rent Growth by Investor Status



Notes: Growth in rent using simple repeat-sales price index methodology without error adjustment for rental listings of investor-owned and non-investor-owned properties. For each series, rent growth is presented in relative terms from 2020Q1. Source: Authors' calculation from CoreLogic MLS Data.

property characteristics described in Section 3.2. Our main coefficients of interest are those on $\Delta Investor_{it}$ that enter into our regression as two indicator variables: $Non \rightarrow Inv$ that is equal to 1 if the property was a non-investor property in the previous listing and an investor property in the current listing and $Inv \rightarrow Inv$ that is equal to 1 if the property was continuously owned by an investor from the previous to the current listing. Thus the omitted category is $Non \rightarrow Non$, which equals 1 if the property was continuously owned by a non-investor.[15]

In column (1), where no fixed effects are included, we see that a property that turns over from a non-investor to an investor experiences around a 5.1 percentage point higher increase in rents compared to properties that are continuously owned by non-investors. Compared

[15]We remove observations that were owned by an investor in the previous listing and no longer owned by an investor in the current listing because this is extremely rare (less than 0.1% of our observations) in the data. This is in line with their strategy of buying properties to be rented out long term.

Table 7. Repeat-Rent Results on Rent Patterns

	(1)	(2)	(3)	(4)	(5)	(6)
				Log(Contract Rent)		
Non→Inv	0.0510***	0.0508***	0.0400***	0.0366***	0.0348***	0.0326***
	(0.00864)	(0.00851)	(0.00696)	(0.00720)	(0.00792)	(0.00828)
Inv→Inv	0.0100***	0.0104***	0.00595*	0.00353	0.00481**	0.00232
	(0.00322)	(0.00343)	(0.00303)	(0.00220)	(0.00215)	(0.00191)
Δ List Year	0.0283***	0.0275***	0.0269***		0.0297***	
	(0.00124)	(0.00111)	(0.00107)		(0.00154)	
ΔInv Pct					0.00328*	
					(0.00173)	
(Non→Inv)*ΔInv Pct					0.00432***	0.00327**
					(0.00136)	(0.00136)
(Inv→Inv)*ΔInv Pct					0.00146	0.00180*
					(0.00165)	(0.00105)
Observations	855,709	855,709	855,709	559,314	749,434	499,665
R-squared	0.123	0.148	0.524	0.712	0.523	0.706
Avg Δ log(*Rent*)	0.060	0.060	0.060	0.060	0.060	0.059
FE	None	YQ	BG-YQ	BG-YQ (t, t-1)	BG-YQ	BG-YQ (t, t-1)

Notes: Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. $Non \rightarrow Inv = 1$ if the property was a non-investor property in the previous listing and an investor property in the current listing and $Inv \rightarrow Inv = 1$ if the property was continuously owned by an investor from the previous to the current listing. Omitted category is $Non \rightarrow Non = 1$ if the property was continuously owned by a non-investor. Not shown are various property and listings characteristics described in Section 3. Data Source: CoreLogic MLS, Tax, and Deeds Data. $\Delta InvPct$ is the change in investor share of SFR properties in the property's block group in the year prior to the listing year, calculated from CoreLogic Tax and Deeds data.

to the sample average of a 6% increase in rents, this amounts to around an 85% higher rate of rent increase. This effect is statistically significant at the 1% level. When we control for our neighborhood-time FEs, this effect decreases to around 4.0 percentage points (column 3). Our most stringent specification in column (4) that controls for both the listing and the previous listing's BG-YQ fixed effects further decreases the effect to 3.7 percentage points, amounting to 60% of the average rent increase.

Meanwhile, properties that are continuously held by investors experience a higher rate of rent increase but not as high as when the properties turn over to an investor. At around 1 percentage point in column (1) to around 0.4 percentage point in column (4), this is less than one-quarter of the effect when the property is first acquired by the investor. Still, it shows that investors do indeed raise rents more, even for properties that they continuously own—around 7-20% of the national rate, depending on the specification.

When we compare within properties that experience a change in ownership (not just investor status), this strong rent effect of properties that are acquired by investors is attenuated but still exists. In Table A2, we restrict the sample to either only properties experiencing ownership change (column 1) or properties experiencing no change in ownership (column 2). In the sample of properties with ownership change, properties that change from non-investor to investor experience around 3.1 percentage point higher rent increase compared to properties that change ownership from non-investor to non-investor. While this magnitude of the coefficients is similar to the coefficient in Table 7, it is smaller relative to the average rent increase of this sample (around 30% relative increase). On the flip side, column (2) shows that properties owned continuously by investors experience 0.7 percentage point higher rent increases than properties owned continuously by non-investors. This amounts to about a 14% higher rent increase. This result is more precisely estimated than in a similar specification in Table 7 column (3).

Overall, the results show that investors raise rents at a higher pace than non-investors. Most of the action comes from properties listed when first acquired by an investor, although properties that are continuously owned by investors still raise rents at higher pace than those owned by non-investors.

3.3.1 Spillovers from Investor Concentration

To examine how other, non-investor SFR rental properties respond to investor entry, we include two additional terms in our repeat-rent specification: the change in the investor-ownership percentage of SFR properties in the block group between two listing periods, $\Delta InvPct$, by itself and interacted with the change in investor status, $\Delta InvPct * \Delta Investor$.

We present the results in Table 7 columns (5) and (6). We see that having a larger percent of SFR properties owned by investors is correlated with higher changes in rent, regardless of the investor status. For all properties, the rent increases are on average 0.3 percentage point higher, or around 5% of the overall average rent increase (column 5) for a percentage point increase in investor share. This effect is more than double for properties that first turn over to investors and is in line with Gurun et al. (2022)'s result that investor-owned properties in locations with higher investor share experience faster rent growth.[16] Our most stringent specification with two sets of fixed effects (column 6) shows a consistent story for properties that first turn over to investors as well as those continuously owned by investors. These results demonstrate that investors can extract higher rents from their properties when there is a higher share of investors in the neighborhood.

3.4 Potential Mechanisms

What allows investors to essentially charge higher rent than non-investors? In this section, we examine four potential mechanisms behind investors' rent-charging behavior: 1) heterogeneous renovation activity and quality improvements, 2) market power in the single family rental market, and 3) investors trading higher rents for higher potential vacancy and turnover (vacancy-rent trade-off).

3.4.1 Renovations

Although our regressions control directly for renovation activity measured by the agent-input public remarks section of listings, we examine heterogeneity in renovation activity by investor type as a potential source of price differences. Even for a set of similar words used to describe renovations, there can be a large degree of heterogeneity in the quality of "renovations" we pick up. If investors engage in higher quality renovation activity and these are not captured by the renovation measure, we will wrongly attribute quality-adjusted rent increases to investor status.

[16] As described in Section 1, their results use a different identification strategy that involves mergers. Moreover, their results indicate that these results occur in locations where a single investor holds more properties. In contrast, our results demonstrate that, regardless of the number of investors, a higher share of investor-owned SFRs contribute to higher rent increases by investor-owned and non-investor SFR rentals.

To explore this idea, we first examine whether investors engage in more renovation activity. Then, we examine whether these renovations to investor-owned properties have higher returns compared to renovations to non-investor properties by including an interaction term $\Delta Investor_{it} * Renovation_{it}$ in our repeat-rent specification in (3). The coefficient on the interaction term estimates the additional returns to renovations performed by investors. If indeed investors engage in more high-quality, high-return renovations, we would expect the coefficient to be positive.

In Table 8 columns (1) and (2), we present results from our regression of renovation activity on investor and corporate indicators. Column (1) includes our standard set of property characteristics and column (2) replaces static property characteristics with property fixed effects. We see that, compared to the omitted category of non-investor, non-corporate owners, both investors and corporate owners engage in more renovation activity. Investors are 5-6 percentage points and corporate owners are 1-2 percentage points more likely to renovate. Compared to the national average, that amounts to more than double the rate of renovation for investors (column 2).

However, Table 8 columns (3) and (4) show that investors are no more likely to capture higher rent returns from their renovations than non-investors. In fact, properties continuously owned by investors have lower returns on renovations compared to their non-investor counterparts. Moreover, the additional inclusion of these interaction terms does not change the story of investors' rent-charging behavior, as noted by the coefficient on $Non \rightarrow Inv$ and $Inv \rightarrow Inv$ not changing from Table 7.

These results present suggestive evidence that investors are not engaging in higher quality or higher-return renovations. However, it must be noted that our measure may miss other margins of heterogeneous renovation activity. For example, any maintenance or renovation activity that is not noted in the public remarks of listings will be missed.

Table 8. Renovation Activity

	(1)	(2)	(3)	(4)
Dependent Var	=1 if Renovated		Log(Contract Rent)	
Investor Flag	0.0550***	0.0644***		
	(0.0129)	(0.0178)		
Corporate Flag	0.0235***	0.0109***		
	(0.00413)	(0.00213)		
Non→Inv			0.0378***	0.0356***
			(0.00573)	(0.00563)
Inv→Inv			0.00678**	0.00481**
			(0.00284)	(0.00209)
Renovated			0.00354**	0.00733***
			(0.00152)	(0.00130)
(Non→Inv)*Renovated			0.0153	0.00620
			(0.0154)	(0.0142)
(Inv→Inv)*Renovated			-0.00819**	-0.0145***
			(0.00337)	(0.00212)
Observations	3,364,335	1,912,804	855,709	559,314
R-squared	0.391	0.823	0.524	0.712
Mean Dep Var	0.106	0.086	0.060	0.060
FE	BG-YQ	BG-YQ, Prop	BG-YQ	BG-YQ(t, t-1)

Notes: Standard errors clustered at the county-level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Investor and corporate flags are defined as in the text. $Non \rightarrow Inv = 1$ if the property was a non-investor property in the previous listing and an investor property in the current listing and $Inv \rightarrow Inv = 1$ if the property was continuously owned by an investor from the previous to the current listing. Omitted category is $Non \rightarrow Non = 1$ if the property was continuously owned by a non-investor. $Renovated = 1$ if we see certain keywords in the public remarks section in the MLS Data. See text for more details. Not shown are various property and listings characteristics described in Section 3, except in column (2)-(4) where static property characteristics are excluded. Data Source: CoreLogic MLS, Tax, and Deeds Data.

3.4.2 Market Power

Related to the spillover channel, we examine whether investors can charge higher rents in locations where they face less competition from other SFR rentals. This is akin to Gurun et al. (2022), where they look at mergers of large players in the buy-to-rent market. However, we focus on a broader sense of market power by looking at the share of SFR rentals in general,

Table 9. Market Power

	(1)	(2)	(3)	(4)
		ΔLog(Contract Rent)		
Non→Inv	0.0550***	0.0544***	0.0427***	0.0386***
	(0.00926)	(0.00908)	(0.00733)	(0.00795)
Inv→Inv	0.00965***	0.0102***	0.00527*	0.00385*
	(0.00341)	(0.00351)	(0.00296)	(0.00229)
Δ SFR Rentals Pct	-0.00183***	-0.00120***	-0.00178***	
	(0.000501)	(0.000296)	(0.000563)	
(Non→Inv)*Δ SFR Rentals Pct	-0.00144**	-0.00154**	-0.00125**	-0.00117*
	(0.000711)	(0.000701)	(0.000484)	(0.000658)
(Inv→Inv)*Δ SFR Rentals Pct	0.000786	0.000644	0.000337	-0.000443*
	(0.000549)	(0.000480)	(0.000274)	(0.000237)
Observations	852,171	852,171	850,870	557,826
R-squared	0.124	0.149	0.527	0.711
Mean Dep	0.060	0.060	0.060	0.060
FE	None	YQ	BG-YQ	BG-YQ (t, t-1)

Notes: Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. $Non \rightarrow Inv = 1$ if the property was a non-investor property in the previous listing and an investor property in the current listing and $Inv \rightarrow Inv = 1$ if the property was continuously owned by an investor from the previous to current listing. Omitted category is $Non \rightarrow Non = 1$ if the property was continuously owned by a non-investor. Not shown are various property and listings characteristics described in Section 3. Data Source: CoreLogic MLS, Tax, and Deeds Data; $SFRRentalsPct \equiv \frac{\#RentalsSFR}{\#SFR} * 100$ from the Census Bureau's American Community Survey (ACS) 5-year estimates from 2006-2010, 2011-2015, and 2016-2020. We linearly interpolate the years in between our ACS measures.

not just those owned by a single investor in a neighborhood.

For this analysis, we augment our repeat-rent specification with an interaction term between change in investor status with change in block group SFR rentals share, $\Delta Investor * \Delta SFRRentalsPct$, where $SFRRentalsPct \equiv \frac{\#RentalsSFR}{\#SFR} * 100$. Our measure of the number of SFR rentals and the number of SFR properties in the block group comes from the Census Bureau's ACS 5-year estimates in 2006-2010, 2011-2015, and 2016-2020.[17]

The results are presented in Table 9. As before, we include a more stringent set of

[17]In order to circumvent using overlapping ACS 5-year summary files, we linearly interpolate the years between our ACS measures. We transform the ACS 2016-2020 estimates, which are provided for 2020 census tract definitions, to 2010 census tract definitions using the procedure described in footnote 23.

neighborhood-time FEs across the columns. Focusing on column (3), which includes BG-YQ FEs and $\Delta Year$, we see that places where rentals are a higher share of SFRs indeed exhibit lower rent growth in general, as do properties that newly turn over to investors. This effect persists for our most stringent specification in column (4), although not it is statistically significant. Overall, there is suggestive evidence that neighborhoods with a higher share of SFRs available as rentals show lower rent growth and investors extract less rent, similar to the results shown in Gurun et al. (2022).

3.4.3 Vacancy-Rent Trade-Off

Finally, we look at the vacancy-rent trade-off channel as a potential source for rent increases: investors may be able to more aggressively raise rents if they are willing to accept the potential loss of tenants. This trade-off may be more acceptable to large-scale investors compared to smaller-scale investors or landlords, whose dependency on a single property's rental income may be larger, and would make them more cautious of potential vacancies from aggressive rent increases. For example, there is evidence in the multifamily rental market that large-scale landlords change their posted rents more often and extract higher rents (Park (2023)).

To explore this idea, we use two methods. First, we explore whether investors have longer days on market (DOM), potentially turning down offers until they meet their posted rent. Second, we see whether investors list the properties for rent more often, allowing them to put their property out in the market either as a means to extract more rent from existing tenants or to replace them with higher paying tenants.

For the first approach of exploring patterns in DOM, we use two specifications: 1) like in the cross-sectional approach, we regress $\log(DOM)$ on investor and corporate flags, and 2) we use the repeat-rent specification, but instead of using change in rent as the dependent variable, we use $\Delta \log(DOM)$. Results for both are presented in Table 10, with the first specification in columns (1) and (2) and the second specification in column (3). In column

Table 10. Vacancy-Rent Trade-Off: Days On Market

	(1)	(2)	(3)	(4)	(5)
Dependent Var	Log(DOM)		ΔLog(DOM)	Turnover	
Investor Flag	-0.00808	0.0136		0.561***	0.164
	(0.0261)	(0.0244)		(0.0765)	(0.144)
Corporate Flag	-0.0214***	0.0177**	0.00376	-0.0772***	-0.199***
	(0.00529)	(0.00881)	(0.00540)	(0.0188)	(0.0742)
Non→Inv			0.0164		
			(0.0240)		
Inv→Inv			-0.0576***		
			(0.0215)		
Observations	3,364,335	1,912,804	1,282,429	435,607	79,803
R-squared	0.494	0.743	0.345	0.401	0.481
Mean Dep Var	82.379	76.454	-0.199	1.596	2.081
FE	BG-YQ	BG-YQ,Prop	BG-YQ	BG-YQ	BG-YQ,Prop

Notes: Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Investor and corporate flags defined as in the text. DOM is Days On Market. Turnover is number of listings per year under the same ownership. Column (3) uses repeat-rent specification on $\Delta Log(DOM)$ instead of rents. Not shown are various property and listings characteristics described in Section 3, except in column (2)-(4) where static property characteristics are excluded. Data Source: CoreLogic MLS, Tax, and Deeds Data.

(1) we include BG-YQ FE and in (2) we additionally include Property FE. These specifications do not show statistically significant evidence that listings for investor-owned properties exhibit differences in DOM. In column (3), there is evidence that properties continuously held by investors actually have lower DOM.

In Table 10 columns (4) and (5), we regress a measure of turnover on investor and corporate flags like in our cross-sectional specification. Our measure of turnover is the number of listings per year under the same ownership. In other words, it is the number of times a property was listed under the same ownership divided by the number of years the property was under the same ownership.[18] In column (4), with BG-YQ FE, we see that investors have a higher number of listings per year. At an average of 1.6 listings per year, investors have around 0.6 more listings per year, or about 38% more than the overall

[18] Note that this is not a perfect measure. Most notably, since we do not necessarily observe all properties to the end of ownership, these measures are censored from the right.

average. In column (5) with property fixed effects added, this effect decreases and is no longer statistically significant, but it is still positive at around 8% higher than the overall average. In contrast, other corporate investors seem to display lower rates of turnover.

Overall, there is no evidence that investors exchange longer listing times for higher rents but there is suggestive evidence that they may list the properties more often to do so.

4 Impact on Neighborhoods

One often-expressed concern is that the entry of large institutional investors into the SFR market is leading to gentrification, particularly of Black and Hispanic neighborhoods.[19] In Section 2, we found that investors have been entering neighborhoods with higher Black population and lower college graduate population shares. In this section, we examine how neighborhoods have changed after investor entry by looking at differences in characteristics of high- versus low-investor share neighborhoods and mortgage borrowers entering and residing in those neighborhoods.

4.1 Changes in Neighborhood Characteristics

First, we look at how several neighborhood characteristics changed during 2010-2020 in tracts with a large investor presence. Specifically, we look at changes in log home value, White population share, college graduate population share, and log median household income. We also construct a composite socioeconomic status (SES) index following Baum-Snow and Hartley (2020). The SES index is based on CBSA-normalized tract-year values of White population share, log median household income, and college graduate population share. The SES index value for the tract-year is the sum of the three normalized component values in that tract-year. The change in the SES index indicates a tract's loss or gain in relative SES

[19] For example, see the opening statement from the Chairman of the House Financial Services Subcommittee on Oversight and Investigations during the hearing, "Where Have All the Houses Gone? Private Equity, Single Family Rentals, and America's Neighborhoods," held in June 2022: https://www.congress.gov/event/117th-congress/house-event/114969/text.

status within the CBSA over the prescribed time period.

We employ both OLS and propensity score matching (PSM) estimation approaches. In the OLS approach, we estimate the equation:

$$\Delta NeighborhoodChar_{bnt} = \beta HighInvInd_{bnt} + \gamma_{n,2010} + \gamma_b + \varepsilon_n, \tag{5}$$

where $\Delta NeighborhoodChar_{bnt}$ is the change in the outcome from 2010 to year $t \in \{2015, 2020\}$ in tract n in CBSA b, γ_b are CBSA fixed effects, $\gamma_{n,2010}$ is a vector of 2010 tract characteristics, and $HighInvInd_{bnt}$ is an indicator for if tract n is a tract with a high investor share ($>$ 1 percent of tract SFRs held by investors) in year t.[20] The 2010 tract characteristics are the same set used earlier in the neighborhood entry regressions (see Table 4).

In the PSM approach, we match investor tracts to non-investor tracts in the same CBSA that are otherwise observably similar based on the 2010 characteristics used as controls in the OLS regressions.[21] We look at the same set of outcomes and use the same treatment indicator as in the OLS estimation. We limit the sample to tracts in CBSAs with some investor presence by 2020.[22]

The results using both estimation approaches for the 2010-2015 and 2010-2020[23] time periods are shown in Table 11 Panels A and B, respectively. Column (1) suggests that home values in high investor tracts increased relative to otherwise similar tracts during 2010-2015, but that result is reversed, although not statistically significant, over the longer 2010-2020 period. Similarly, the results for log median household income are suggestive of a small increase in income in investor and high investor tracts during 2010-2015, but the other way

[20]Because there are virtually zero investor-owned properties in 2010, this amounts to an indicator variable that equals one for places where the level of change from 2010 to year t is above 1 percent.

[21]PSM Average Treatment Effect on the Treated (ATT) is estimated using an exact match on CBSA.

[22]High investor tracts make up 6 percent and 10 percent of tracts in the sample in 2015 and 2020, respectively. The full sample comprises 55,768 tracts and 408 CBSAs, including tracts in every state in the contiguous US.

[23]We use a geographic crosswalk constructed by IPUMS NHGIS (https://www.nhgis.org/geographic-crosswalks) to convert the 2020 census geographies provided in the 2020 summary file to 2010 geographies, which are used in the 2010 and 2015 summary files. We use the 2020 block group to 2010 block group crosswalk in conjunction with 2020 block group-level ACS data and then aggregate to the tract level in order to be as accurate as possible in the transformation.

over 2010-2020.

The results for White population share and college graduate population share are more consistent across time periods, which indicates a relative decrease in White population share and college graduate share. Using the composite SES index, we see a statistically significant but small relative decrease in overall SES status for investor tracts, with larger effects for the 2010-2020 period. The PSM estimate for 2010-2020 implies an average relative decrease of 21 percent of the standard deviation of ΔSES index, compared to 9 percent of the standard deviation of ΔSES index during 2010-2015.

These results could still be consistent with a gentrification hypothesis if the decrease in SES status is driven solely by the changing mix of homeowners and renters in the neighborhood due to the increase in supply of rental SFRs. In other words, an increase in the share of renters, who tend to be lower SES compared to homeowners on average, could mask an increase in SES status among homeowners and renters in high investor areas where home values may have increased.

To explore this, we use the ACS data to separately analyze homeowners and renters by constructing separate SES indices for each group.[24] Figure 4 shows the OLS (Panel A) and PSM (Panel B) estimation results for 2010-2015 and 2010-2020.[25] Both estimation approaches indicate a decrease in SES standing among homeowners. Relative to other homeowners in their metro area, homeowners in high investor tracts less likely to be White and be college graduates by 2015, and by 2020, they also had smaller household income growth. Homeowners in high investor tracts fell in SES standing, as measured by their change in the

[24]In order to do so, we alter our SES component measures slightly. Instead of the White share of the population, we use the share of owner-occupied or renter-occupied housing units whose householder is White. Similarly, for college graduate share, we use the share of owner-occupied or renter-occupied housing units whose householder is a college graduate. Since we do not change the right hand side of the previous estimation equation, we continue to use 2010 characteristics of the entire tract as controls in the OLS estimation and as the matching variables in the PSM estimation.

[25]The ACS summary file does not report median household income and college education status by homeowner/renter status at the block group-level. Consequently, we cannot use the approach in footnote 23 to transform 2020 ACS measures to 2010 tract definitions. Instead, for those two measures we generate our own geographic crosswalk by mapping all current residential properties in the CoreLogic Tax data into 2010 and 2020 tracts. From that we can generate a 2010 tract-to-2020 tract crosswalk that enables us to transform the 2020 tract data to 2010 tract definitions.

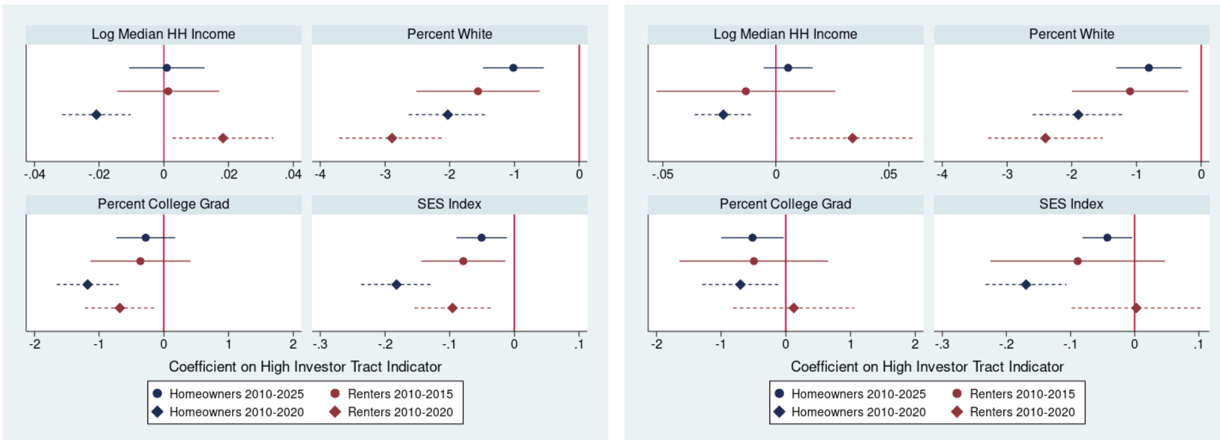
Table 11. Neighborhood Change in Tract with High Investor Share, 2010-2015 and 2010-2020

Panel A: 2010-2015					
	(1)	(2)	(3)	(4)	(5)
Dependent Var:	ΔLog Home Value	ΔLog Median HH Income	ΔWhite Pop Share	ΔCollege Grad Share	ΔSES Index
Treatment:	*2015 Investor SFR Share > 1%*				
PSM	0.0235**	0.00761	-1.305***	-0.832***	-0.0808***
	(0.0100)	(0.00802)	(0.366)	(0.174)	(0.0261)
OLS	0.0315***	0.00442	-1.525***	-0.568***	-0.0911***
	(0.0102)	(0.00614)	(0.353)	(0.136)	(0.0236)
SD 2010 -2015 Chg	0.18	0.18	8.29	5.99	0.78
N	55,768	55,768	55,768	55,768	55,768
Treated N	3,531	3,531	3,531	3,531	3,531
Panel B: 2010-2020					
	(1)	(2)	(3)	(4)	(5)
Dependent Var:	ΔLog Home Value	ΔLog Median HH Income	ΔWhite Pop Share	ΔCollege Grad Share	ΔSES Index
Treatment:	*2020 Investor SFR Share > 1%*				
PSM	-0.0198	-0.0144**	-2.422***	-0.950***	-0.180***
	(0.0137)	(0.00627)	(0.491)	(0.216)	(0.0321)
OLS	0.0145	-0.0147***	-2.749***	-1.302***	-0.222***
	(0.00949)	(0.00517)	(0.430)	(0.225)	(0.0307)
SD 2010-2020 Chg	0.24	0.22	9.82	7.37	0.95
N	55,768	55,768	55,768	55,768	55,768
Treated N	5,520	5,520	5,520	5,520	5,520

Notes: *** p<0.01, ** p<0.05, * p<0.1. This table shows Ordinary Least Squares (OLS) results from equation 5 and the analogous Propensity Score Matching (PSM) results. In OLS, 2010 tract characteristics controlled for along with Core-Based Statistical Area (CBSA) fixed effects. Standard errors clustered on CBSA. In PSM, tracts matched on 2010 characteristics and exact match on CBSA. Tracts not in a CBSA or that are in a CBSA with no investor presence by 2021 are excluded. Data Source: CoreLogic MLS, Tax, and Deeds Data; with the exception of home values, which are sourced from the Zillow Home Value Index, the 2010, 2015, and 2020 characteristics are sourced from the 2010, 2015, and 2020 American Community Survey (ACS) 5-year summary files, respectively. We use a geographic crosswalk constructed by IPUMS NHGIS (https://www.nhgis.org/geographic-crosswalks) to convert the 2020 census geographies provided in the 2020 summary file to 2010 geographies, which are used in the 2010 and 2015 summary files. We use the 2020 block group to 2010 block group crosswalk in conjunction with 2020 block group-level ACS data and then aggregate to the tract level in order to be as accurate as possible in the transformation. SES index constructed by summing tract-year values of White population share, college graduate share, and log median household income normalized within CBSA.

Figure 4. Change in Characteristics of Homeowners and Renters in Tracts with High Investor SFR Share, 2010-2015 and 2010-2020

(a) OLS **(b)** PSM



Notes: N = 46,547. Error bars display 95 percent confidence intervals. In Panel A, 2010 tract characteristics controlled for along with Core-Based Statistical Area (CBSA) fixed effects. Standard errors clustered on CBSA. In Panel B, tracts matched on 2010 characteristics and exact match on CBSA. Tracts not in a CBSA or that are in a CBSA with no investor presence by 2021 are excluded. Data Source: White householder share, college graduate householder share, and median household income for homeowners and renters are sourced from ACS; the SES index for homeowners and renters is constructed by summing tract-year values of White householder share, college graduate householder share, and log median household income normalized within CBSA.

SES index from 2010-2015 and 2010-2020.

Renters in high investor tracts were also relatively less likely to be White compared to other tracts in the metro area. However, in contrast to homeowners, renters show a relative increase in household income by 2020. This is consistent with a shift in composition of renters toward SFR renters (who tend to be higher income than non-SFR renters) in high investor tracts as well as the larger rent increases levied by investors compared to other owners. The 2010-2020 SES index change for renters in high investor tracts is sensitive to specification, but in both specifications the change is more positive than it is for homeowners.

4.2 Changes in Characteristics of Mortgage Borrowers

In this section we examine changes in neighborhoods through the lens of mortgage borrowers, for both purchases and refinances. This allows us to disentangle changes in homeowner characteristics shown in Figure 4 between households more likely to be new to the neighborhood (homebuyers) versus households tenured in the neighborhood (refinancers). While mortgage borrowers may not be representative of the average in-mover and incumbent homeowners due to selection into mortgage borrowing,[26] if we assume that the patterns of selection are relatively stable over time between low- and high-investor tracts, these results can provide a look into changes in entering and incumbent homeowners.

For this analysis we examine the 2012-2021 period using Home Mortgage Disclosure Act (HMDA) data on new purchase mortgage originations and refinances.[27] We use the following event-study-type specification to examine the evolution of purchase and refinance mortgage borrowers:

$$Orig_{bnt} = \sum_{j=2013}^{j=2021} \beta_j (HighInvInd_{bn,2021} * D_j) + HighInvInd_{bn,2021} + \gamma_{n,2010} + \gamma_t + \gamma_b + \gamma_{bt} + \varepsilon_{nt}, \tag{6}$$

where $HighInvInd_{bn,2021}$ is an indicator that equals one if tract n in CBSA b is a high investor tract in year 2021, $\{D_j\}_{j=2013}^{2021}$ is a set of dummy variables for each $j \in [2013, 2021]$, $\gamma_{n,2010}$ is a vector of 2010 tract characteristics, γ_t are year fixed effects, γ_b are CBSA fixed effects, and γ_{bt} are CBSA-year fixed effects. $Orig_{bnt}$ is one of three outcomes: White share, Black share, or log median income of borrowers separately for purchase mortgages and refinances in CBSA b, tract n, and year t.[28] We again limit the sample to tracts in CBSAs that had some investor presence. Our coefficient of interest are $\{\beta_j\}$, which estimates year j's changes in the difference in $Orig_{bnt}$ between high-investor tracts and low-investor tracts relative to their baseline difference in 2012.

Figure 5 plots the coefficients on the interactions terms ($\beta_{2013}, \beta_{2014}...\beta_{2021}$) for each of the three outcomes for purchase mortgage originators and refinancers. In Panel A, we see a

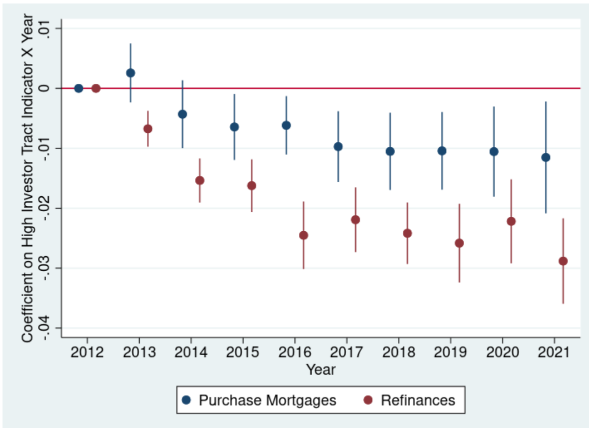
[26]See, for example Gerardi et al. (2020) for differential selection into refinancing by borrower race.

[27]HMDA data provides a comprehensive view of the US mortgage market, covering over 90 percent of residential mortgage originations in the U.S. (CFPB (2018)).

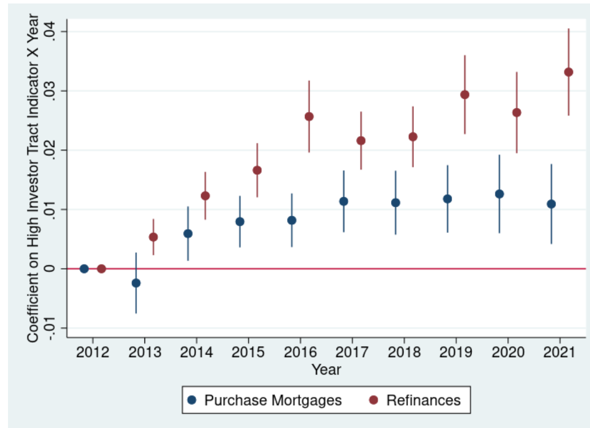
[28]We identify the race associated with a purchase mortgage or refinance as White or Black only if all applicants are recorded as such in the HMDA data. In the small number of cases where there is a co-applicant but the race of the co-applicant is missing, we use the race of the applicant.

Figure 5. Change in Characteristics of Purchase Mortgage Originations and Refinances in Tracts with High Investor SFR Share, 2012-2021

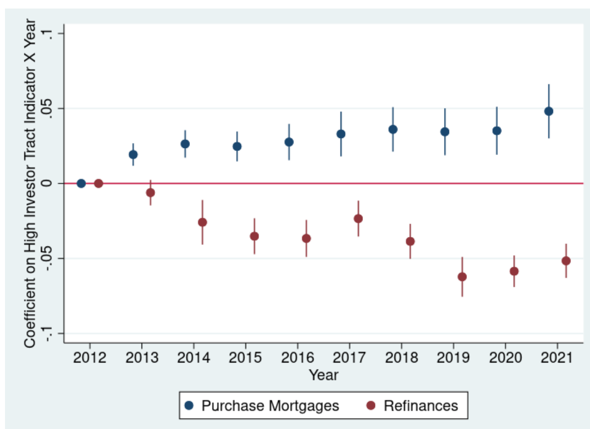
(a) White Share



(b) Black Share



(c) Log Income



Notes: N= 488,871. Error bars represent 95 percent confidence interval based on standard errors clustered on Core-Based Statistical Area (CBSA). CBSA, year, and CBSA-year fixed effects and vector of 2010 tract characteristics are included in the regressions. Tracts not in a CBSA or that are in a CBSA with no investor presence by 2021 are excluded. Data Source: Characteristics of purchase mortgage and refinance originators sourced from HMDA data. Tract characteristics sourced from 2010 American Community Survey and Zillow Home Value Index.

relative decrease in the White share of new purchase mortgages in high investor neighborhoods and an even larger decrease among refinances. Panel B shows close to a mirror image of the Panel A results—there is a relative increase in the Black share in high investor tracts among new purchase mortgages and a larger increase among refinances. In both the White share and Black share results, the differential impact in high investor tracts continues to grow over time until about 2017, when it starts to level off. These results are consistent with Austin (2022), who uses a merger specification to explore changes in the race and ethnicity of home purchase mortgage applications and originations in Atlanta.

In Panel C, we find diverging income trends among borrowers of purchase and refinance mortgages. Refinancers in high investor tracts appear to have lower relative income compared to other neighborhoods in the metro, while purchase borrowers exhibit higher relative income. This suggests that high investor tracts are attracting more higher-income homebuyers but tenured homeowners may be experiencing weaker relative income growth. Interestingly, this is entirely consistent with the homeowner results in Figure 4: the opposite relative change in median income between movers/purchasers (positive) and stayers/refinancers (negative) seems to cancel out to create a zero effect in the earlier period, 2010-2015, while the more negative effect of stayers is consistent with the negative effect for the latter period, 2010-2020.

Overall, the results suggest that homeowners in high-investor-share neighborhoods are relatively less likely to White over time compared to other neighborhoods in their metro area and that there is a divergence in income trends between movers and stayers. They also suggest the change in the racial makeup of homeowners is coming from a combination of an increase in the likelihood of non-White households to remain in high investor tracts relative to other tracts as well as a shift in the racial composition of new homebuyers in high investor tracts.

5 Conclusion

In this paper, we examined the activity of a relatively new class of Wall Street buy-to-rent investors on three dimensions: their entry behavior, rent-charging patterns, and impact on neighborhoods post-entry.

We documented several facts surrounding their overall participation in the SFR market, especially that their entry has accelerated in recent times, especially into neighborhoods of lower housing value but with higher shares of higher-income and minority individuals. In recent years, investors have tended to enlarge their presence in areas they previously entered as opposed to entering new neighborhoods. Most notably, we show that investors charge higher rents, particularly when they first turn over the property. We do not find evidence of gentrification following investor entry, as high investor neighborhoods became relatively less White and less college educated compared to other neighborhoods in the metro area.

Much of the focus on these investors has swayed to either extreme. It is an open question how factors explored in this paper contribute to the overall welfare of renters or homeowners. While it may be that these investors are playing a role in supplying SFR rentals and opening up neighborhoods to households who are credit constrained, they are also accelerating the pace of rent increases and are more aggressive in seeking out new renters in order to do so. Moreover, neighborhoods are not experiencing increased gentrification as feared by some policymakers, but these effects are different across home buyers, incumbent homeowners, and renters along some margins. Finally, as investors shift away from acquiring distressed properties to other sources, the traditional stock of homes available for homeownership may be decreasing if investors have a leg up on placing more aggressive, cash-only bids.[29]

Future work will need to better incorporate these factors in assessing welfare more comprehensively. Crucially, policymakers will also need to balance the need to meet rental demand, the decrease in the supply of homes available for homeownership, and rent increases that follow investor entry.

[29] See Reher and Valkanov (2023) for the exceptionally large cash-only discount in purchase offers.

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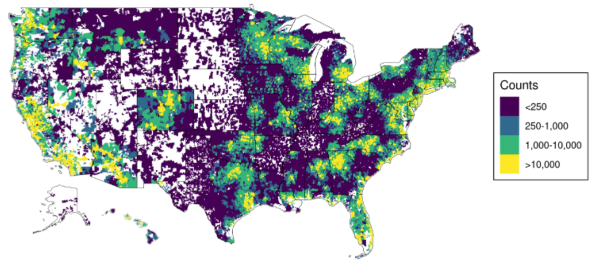
A Appendix Figures and Tables

Appendix Figure A1. MLS Coverage by Zip Code



Note: This figure plots counts listings by Zip Code in four count categories across the United States. Source: Authors' calculation from CoreLogic MLS Data.

Appendix Table A1. Comparison of Counts With Amherst Capital Report

Investor	Amherst Capital Count 2020 (000s)	Our Count 2020 (000s)
Invitation Homes	76.0	82.0
American Homes 4 Rent	48.6	55.0
Progress Residential	32.8	50.6
Cerberus Capital Management	24.2	34.9
Main Street Renewal	23.0	29.9
Tricon American Homes	18.6	25.8
Home Partners Of America	14.4	19.1
Front Yard Residential	11.8	12.7
Connorex-Lucinda	8.2	10.2
Vinebrook Homes	7.0	9.9
Gorelick Brothers Capital	2.5	2.9
Camillo Properties	1.6	6.9
Lafayette Real Estate	1.5	0.9
Golden Tree Insite Partners (GTIS)	1.2	
Havenbrook Homes	1.1	
Prager Property Management	1.1	
Reven Housing Reit	0.8	0.9
Other	1.9	

Source: Amherst Capital Count from Amherst Capital's 2021 report on investor-held single family rents (Bordia et al. (2021)). Our Count is from authors' calculations from CoreLogic Tax and Deeds Data.

Appendix Table A2. Repeat-Rent Results on Rent Patterns for Properties with Similar Ownership Change Status

	(1)	(2)
Sample of Properties with:	Ownership Change	No Change
Non→Inv	0.0308***	
	(0.00924)	
Inv→Inv	-0.000361	0.00669***
	(0.00681)	(0.00208)
Δ List Year	0.0257***	0.0257***
	(0.00187)	(0.000913)
Observations	89,003	652,006
R-squared	0.659	0.506
Avg Rent Change	0.098	0.051
FE	BG-YQ	BG-YQ

Notes: Standard errors clustered at the county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. $Non \rightarrow Inv = 1$ if the property was a non-investor property in the previous listing and an investor property in the current listing and $Inv \rightarrow Inv = 1$ if the property was continuously owned by an investor from the previous to the current listing. Omitted category is $Non \rightarrow Non = 1$ if the property was continuously owned by a non-investor. Not shown are various property and listings characteristics described in Section 3. Data Source: CoreLogic MLS, Tax, and Deeds Data.