Keeping Up with the Blackstones: Institutional Investors and Gentrification

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Abstract

Policy makers worry that institutional investment in residential real estate drives up house prices and crowds out minority residents. Using mergers of private-equity backed firms to isolate quasi-exogenous variation in concentration of ownership at the neighborhood level, I find that shocks to institutional ownership indeed cause higher prices and rents — but, contrary to popular opinion — increase rather than decrease neighborhood diversity. The reason for increased diversity is that some minorities benefit from the relaxation of borrowing constraints as a result of higher house prices and take out mortgages for home improvement, increasing the attractiveness of their homes; other minorities move in because more rental properties become available as institutional ownership crowds out predominantly white individual home ownership. Institutional investors benefit from increased market values of their houses in increasingly attractive neighborhoods, but also extract value by challenging tax assessors' valuations and thus reduce their tax bill by an estimated $4.1b nationwide. This is a hitherto unknown source of rent extraction by institutional investors. I conclude that policy makers are right to be worried about some aspects of institutional investment in residential real estate, but they are mostly worried about the wrong thing.

JEL: G11, G23, M20, R30

Keywords: Housing, Private equity, Real estate, Gentrification

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Abstract

Policy makers worry that institutional investment in residential real estate drives up house prices and crowds out minority residents. Using mergers of private-equity backed firms to isolate quasi-exogenous variation in concentration of ownership at the neighborhood level, I find that shocks to institutional ownership indeed cause higher prices and rents — but, contrary to popular opinion — increase rather than decrease neighborhood diversity. The reason for increased diversity is that some minorities benefit from the relaxation of borrowing constraints as a result of higher house prices and take out mortgages for home improvement, increasing the attractiveness of their homes; other minorities move in because more rental properties become available as institutional ownership crowds out predominantly white individual home ownership. Institutional investors benefit from increased market values of their houses in increasingly attractive neighborhoods, but also extract value by challenging tax assessors' valuations and thus reduce their tax bill by an estimated $4.1b nationwide. This is a hitherto unknown source of rent extraction by institutional investors. I conclude that policy makers are right to be worried about some aspects of institutional investment in residential real estate, but they are mostly worried about the wrong thing.

JEL: G30, G34, J71, L26, M13, M14

I. Introduction

Invitation Homes has virtually no ability to impact broader rent trends in its communities... What's more, the notion that a company that represents less than 0.1 percent of the single-family homes in America is having a significant impact on this market is not based in fact.

Blackstone, November 2019

Concentrated ownership is often viewed as dangerous, because it may generate market power that facilitates exploitation; conversely, it may increase welfare by generating efficiencies. Research into this trade-off informs the regulation of take-overs and of monopolistic enterprises. On the one hand, horizontal mergers may concentrate ownership and allow inefficient price increases that increase corporate profits at the expense of consumer surplus (Farrell and Shapiro (1990), Brueckner and Spiller (1991), Ashenfelter and Hosken (2010)). On the other hand, concentrated owners may operate at a sufficiently large scale to achieve productivity gains that benefit consumers (Daughety (1990), Sapienza (2002)).

In recent years, questions relating to ownership concentration have become salient in the residential property market. Since the Great Recession, private-equity backed institutional investors have acquired over 300,000 single-family homes across the United States and have converted them to rental properties.[1] In doing so, they have created geographically concentrated residential property investment portfolios. The above Blackstone quotation therefore gives a potentially misleading impression: within the neighborhoods where they invest, private equity firms own significantly more than 0.1% of the single-family homes. The emergence of institutional ownership created a significant change in the ownership structure of neighborhoods where it has occurred. In June 2022, the US

[1] American Homes 4 Rent in their S-11 in 2013 noted that 'According to JBREC, for every 1.0% decline in the homeownership rate, the occupants of approximately 1.1 million homes become prospective tenants. '

Congress Financial Services Committee expressed concern that this change might have raised rents and house prices, while also decreasing minority home ownership.[2]

In this paper, I use a unique dataset of private equity investment in the residential housing market in Atlanta, GA, to investigate the effects of concentrated ownership. I examine four mergers that resulted in substantial, and quasi-exogenous, variation in ownership concentration of single-family housing in Atlanta. I argue that the mergers were plausibly exogenous to local economic conditions in Atlanta. I use a staggered difference-in-differences approach to study the effect that the mergers had upon rent, house prices, housing quality, and neighbourhood demographics. My analysis uncovers a new benefit of ownership concentration: when they decide how much to spend on improvements to their property portfolios, concentrated owners internalize more of the communal benefits that their investment brings to their neighborhoods. Consequently, concentrated owners may spend more on home improvements. I find that rents increase by 5.0% increase and house prices by 3% in the four years following a merger. And, because those price increases relax credit constraints for owner occupiers, I find that they apply for more home-improvement loans and permits. Contrary to the concerns expressed by Congress, neighbourhoods in which there is concentrated private equity ownership exhibit greater racial and socio-economic diversity. I also find that institutional owners use their economies of scale to more successfully appeal tax assessor valuations. These appeals reduce institutional investors' tax bills by an estimated $4.1b nationwide.

In order to conduct my analysis, I collate the ownership history and annual tax valuations of all single-family properties in fifteen counties in Atlanta, GA, via Freedom of Information Act (FOIA) requests. This tax data provides a detailed history of each property including an assessment of the condition/quality of the property, as well as disaggregated house and land valuations. I merge this ownership history with institutional ownership data collected from SEC filings and OpenCorporates. To further examine the

[2] The Committee aimed to know the role of institutional investors in raising rents and house prices, decreasing minority home ownership, "displacing residents of colour and leading to the gentrification of these communities." from the opening remarks of Rep. Al Green, Chair of the Sub-Committee for Oversight and Investigations of the House Committee on Financial Services in the Hearing 'Where Have All the Houses Gone? Private Equity, Single Family Rentals and America's Neighborhoods'.

impact of institutional ownership on housing quality, I combine this property ownership dataset with detailed home permit records obtained from the City of Atlanta. I merge this individual property-level dataset with neighborhood-level data including house price and rent indices obtained from Zillow and neighborhood characteristics obtained from the Census Bureau's American Community Survey. I examine changes at the neighborhood-level in terms of borrowing for home improvements and neighborhood demographics using mortgage applications and originations obtained from the Consumer Financial Protection Bureau's Home Mortgage Disclosure Act (HMDA) database. Finally, I identify the mergers used for this analysis using CapitalIQ.

I use merger data in order to identify a causal connection between observed changes in ownership concentration and neighborhood outcomes. Mergers and acquisitions of geographically dispersed portfolios have long been recognized as a means of isolating the differential local impact of changes in ownership concentration (Hastings (2004)). Similar to the approach in Gurun et al. (2022), I use national mergers between institutional investors that occur for reasons that are plausibly unrelated to local portfolio composition. Ownership concentration that changes in a given residential neighborhood as a result of such a merger is arguably exogenous to the underlying economic conditions of that neighborhood. The main challenge to this identification assumption is that the decision to merge may be endogenous: that is, acquirers may select targets whose portfolios they expect to perform well in the future. If acquirers do create value in this way, then the target's property portfolio should exhibit outperformance regardless of any change in ownership concentration that occurs as a result of the merger. I test for this possibility by showing that this outperformance does not occur in neighborhoods in which only the target owns property pre-merger. This suggests that my results are driven by changing competitive dynamics and not by target portfolio selection. I also consider an announced (but failed) merger as a placebo to my analysis. An alternative potential criticism of this empirical strategy is post-merger neighbourhood outperformance may be driven not by changing competitive pressures but, rather, by the aquirer's ability to select neighbourhoods that will experience greater price appreciation or quality improvements. I control for this potential selection effect, by comparing neighborhoods where the acquirer gained properties in the merger with those where the acquirer already owned properties but the target did not.

I directionally confirm existing findings that institutional ownership correlates with higher prices (Lambie-Hanson et al. (2019),Mills et al. (2019) and Gurun et al. (2022)). I find a 5.0% increase in rents and a 3.0% increase in house prices in the four years following a merger in neighborhoods with greater overlap between the acquirer's and target's portfolios relative to neighbourhoods where the acquirer already owned houses, but the target did not. This result holds after controlling for time-varying characteristics at the county-level and fixed neighborhood characteristics.

Next, I examine the impact of mergers on housing quality. Higher house and rental prices relax households' borrowing constraints which induces greater spending on home improvements by owner occupiers and investors that own less than ten properties (hereafter 'small' investors). In the four years following a merger, applications for home improvement loans by owner occupiers are 54% higher in value in neighborhoods in which there was a change in concentration as a result of an institutional merger. This adds a new channel to the finding in Cloyne et al. (2019) that households increase borrowing in response to house price increases. To further investigate household improvements following mergers, I examine the building permits obtained by different types of property owners following mergers. I find that owner occupiers and small investors apply for more permits for home improvement following an institutional merger in their neighborhood. Specifically, 78% more permits are issued to owner occupiers and 47% more permits to small investors in neighborhoods that experience an increase in institutional ownership post-merger.

Property valuations for tax purposes provide no evidence that institutional investors make more home improvements to properties in areas in which they have an increased market share as a result of a merger. In fact, I find that acquirer-owned properties experience 2.5% lower tax assessor valuations post-merger than properties in the same neighborhood, controlling for neighborhood-year fixed effects. I rationalize this finding through forensic examination of tax appeals. Institutional owners may take advantage of economies of scale in a region by employing in-house legal services and property assessors that enable the institutional investor to more efficiently appeal tax assessments. Consistent with this hypothesis, I find institutional investors appeal property valuations with a frequency of 16.8% (over 18 times the rate at which owner occupiers appeal). Institutional investors are more successful in their appeals than owner-occupiers and there is no difference in the financial benefit of successful appeals. That is, the reduction in valuation obtained on successful appeal is no different between owner types once I control for the size of the appeal.[3] I use realized sales to investigate whether these appeals create a misalignment between taxable valuation and market price. I find the difference between property valuation and sale price is over four times higher for institutional investors than owner occupiers, even controlling for neighborhood-year characteristics and the number of previous appeals on the property valuation. This finding suggests that institutional investors may use tax appeals to decrease the valuations of properties in their portfolios, and hence reduce the local tax paid on those properties. These appeals are economically significant. Assuming a property tax rate of 1% and the median difference between tax and realized (sale) valuation, institutional investors are saving \$4.1b in tax payments across all institutional-owned properties in the United States. This hitherto unknown source of rent extraction by institutional investors.

Higher rent prices creates a greater supply of rental housing which generates greater racial and socio-economic diversity in neighborhoods. High house prices do not reduce diversity of home loan applications or approvals. Loan application rates from Black/African American and Latino/Hispanic applicants are 17.9% and 23.4% higher, respectively, in neighborhoods that experienced a large increase in concentration of ownership as a result of an institutional merger. Mortgage origination rates in these neighborhoods are similarly 15.4% and 20.8% higher for Black/African American and Latino/Hispanic bor-

[3] Institutional investors experience lower reductions in valuations in absolute terms. This is unsurprising given the frequency with which they appeal (i.e. there is less time for the tax assessor valuation to become substantially misaligned from the owner's valuation). However, once I control for the difference between the taxpayer's valuation and the tax assessor's valuation (i.e. the "size" of the appeal), there is no difference in the size of the reduction in valuation (i.e. the degree of success of the appeal).

rowers. Rather, it is White non-Hispanic and Mixed Race applicants who reduce their demand for housing in neighborhoods that experience an increase in institutional investor concentration of ownership. White and Mixed Race application rates are 6.7% and 20.8% lower, respectively, in neighborhoods that experience a large increase in concentration of institutional investor ownership. These findings are robust to the inclusion of a number of controls for housing supply, changes in rental supply, house prices, etc. These results are suggestive that increased supply of rental housing following institutional mergers correlates with greater neighborhood diversity.

This paper contributes to a growing literature on the impact of institutional investors on single-family housing markets. Smith and Liu (2020) find that institutional investors were able to acquire properties at a significant discount to other purchasers, and Ganduri et al. (2022) find that institutional investors stabilized prices in distressed neighborhoods during the Great Recession. Recent work has found that regions with higher institutional ownership have lower home ownership rates and higher house and rental prices (Lambie-Hanson et al. (2019) and Mills et al. (2019)). Gurun et al. (2022) uses a subset of the mergers examined in this paper to show that increased concentration of institutional ownership increases prices and rents, and reduces neighborhood crime.

The paper proceeds as follows. Section Two provides further institutional details and a literature review. Section Three presents the theoretical framework and develops the key empirical predictions of the model. Section Four describes the data and classifications used in the empirical analysis. Section Five contains the empirical analysis. Section Six concludes.

II. Institutional Details and Literature Review

Institutional ownership of single family rental properties has grown 3% annually since 2010. Institutional purchases are not confined to distressed acquisitions in the post-Great Recession period. In fact, institutional investors added 27% to their housing stock between 2018-2021, with the third quarter of 2021 having the largest ever year-on-year increase in purchases.[4] Before the financial crisis, there were approximately 10 million single family rental homes across the United States that were predominantly owned by small 'mom and pop' investors, each of whom owned 10 homes or less. As late as 2011, no single investor in the United States owned more than 1,000 homes (Christophers (2021)). Institutional investors entered the market in 2012 and began purchasing homes across the United States. The vast majority of these homes were acquired in single asset purchases.[5] By mid-2021, the largest institutional investors owned over 280,000 homes across the United States, with some estimating the that institutional investors owned upwards of 700,000 properties, about 5% of the overall market of 14m rental homes in the United States.[6]

Institutional investors tend to cluster their purchases in areas in which they can obtain economies of scale. As early as 2016, Invitation Homes acknowledged that more than 95% of their revenue would come from markets in which they owned at least 2000 properties.[7] Similarly, Colony Starwood noted that they had approximately 2,800 homes in each of their largest markets, and that they would continue to expand their holdings in these markets and would only expand into other areas where they could acquire 'the critical mass of homes that management believes is necessary to maximize operational efficiency.'[8] Hence, while SFR ownership represents a small percentage of overall housing ownership,

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4 See the disclosures made to the House Financial Services.

5 Invitation Home's S-11 statement notes that they 'have largely avoided bulk portfolio acquisitions... Our acquisition teams have acquired 94% of our [homes] in single-asset acquisitions. Similarly, both Colony American and American Homes 4 Rent acknowledge that their primary acquisition channels are MLS listings, our strategic relationships in our core markets, home builders, foreclosure auctions and short sales. However, both acknowledge that they 'may opportunistically identify and pursue bulk portfolios of homes from other SFR companies, government sponsored enterprises, private investors, banks, mortgage servicers and other financial institutions. ' Colony Starwood 10-K Bulk acquisitions have become more common through purchase of assets from other SFR providers or mergers. Nevertheless, across the five major SFR providers, only 21.9% of their homes were acquired through bulk sales (according to disclosures made to the House Committee on Financial Services available.

6 More information from HousingWire Wall Street SFR firms accused of stripping equity from neighborhoods

7 Invitation Homes' S-11 statement says 'More than 95% of our revenue for the three months ended September 30, 2016 was earned in markets where we have at least 2,000 homes, driving significant operational efficiency. '

8 Colony Starwood's 2016 10-K report states 'SFR portfolio had an average of approximately 2,800 homes in each of our 10 largest markets. Management...expects to further expand our depth in markets currently represented in our SFR portfolio and... [other markets] where we will be able to establish the requisite critical mass of homes that management believes is necessary to maximize operational efficiency.'

it is highly concentrated in several geographic regions that experienced high levels of foreclosures during the Great Recession. Furthermore, the existing fragmentation in the SFR market enabled institutional investors to gain significant market power without owning a significant market share.[9]

One means for institutional investors to amass a larger market share in housing markets is through mergers or acquisitions of existing portfolios. I use four such mergers to examine the impact of increased concentration of institutional ownership on neighborhood characteristics. Economic theory provides us with two predictions of the impact of horizontal mergers on local markets. First, mergers reduce competition and may enable firms to raise prices (Farrell and Shapiro (1990), Brueckner and Spiller (1991)). Second, mergers may increase efficiencies through economies of scale and productivity improvements (Daughety (1990), Sapienza (2002)). In the single family rental market, mergers could increase efficiency through synergies (for example, consolidation of overlapped functions, e.g. property management divisions) and productivity gains (e.g. technology used for property valuations and estimates of required improvements). Indeed, institutional investors cite complementarities with their existing portfolio and economies of scale as the key drivers for each of the mergers used in this analysis.[10]

Institutional investors state that their presence may improve the neighborhoods in which they operate. For example, Invitation Homes states 'the investments we make, and the high standard to which we renovate our homes, improve our local communities both by offering residents choice and access to a superior quality of living and by driving local employment.'[11] In this paper, I examine three different channels through which increased

[9] Institutional SFR owners point to market fragmentation as an attractive characteristic that has been key to their business success: American Homes 4 Rent notes in its S-11 that 'Historically, the single-family home rental market has been extremely fragmented, comprised primarily of private and individual property investors in local markets. Until recently, there have been no large-scale, national market owners/operators... [with] an unprecedented opportunity to acquire a large number of homes at attractive prices.'

[10] For example, Tricon American note in relation to the acquisition of Silver Bay Realty Trust that the 'combination of two geographically complementary SFR portfolios is expected to unlock substantial operating benefits and efficiencies... in particular given the geographic overlap in the Sun Belt' and will achieve synergies 'through two primary channels: (i) property-level efficiencies arising from enhanced operating scale in each market... and (ii) general and administrative expense synergies through the elimination of corporate-level redundancies.'

[11] S-11 statement

concentration of institutional ownership may impact gentrification of local communities. First, institutional investors may make more improvements to houses in neighborhoods in which they own a higher market share, especially if mergers create increased bargaining power with local tradespeople (e.g. builders). Such construction works or visible home improvements may have a spillover impact on the home improvement decisions of other homeowners in the neighborhood. Second, if a merger results in higher rent and house prices, there may be a wealth effect for other homeowners in the neighborhood which encourages greater expenditure on home improvements.[12] Finally, institutional investors may indirectly improve neighborhoods through consistent payment of taxes that support local councils to make improvements.[13]

As noted above, this paper is most closely connected to the literature on the role of institutional investors in the single family housing market. This research sits within the broader literature on how private equity investment impacts the industries in which it invests. Research has found private equity buyouts increase price (Chevalier (1995)) and lower product quality (Matsa (2011)) in supermarkets, increase tuition in higher education providers (Eaton et al. (2019)), increase mortality in nursing homes (Gupta et al. (2021)), lower local governance content and reduce editorial staff in newspapers (Ewens et al. (2021)). Gandhi et al. (2021) find that private equity backed companies compete more aggressively in competitive markets and exploit their market power in less competitive ones. Furthermore, this paper relates to studies on the ESG impact of private equity investments. Private equity ownership reduces health violations (Bernstein and Sheen (2016)) and workplace injuries (Cohn et al. (2021)), increases product offerings across geographies (Fracassi et al. (2020)), but decreases employee satisfaction across a range of industries (Lambert et al. (2021) and Gornall et al. (2021)).

Finally, my study contributes to a growing literature on the causes and impacts of gentrification on communities. Gentrification increases local house prices, which benefits

[12] For example, Carroll et al. (2011) and Case et al. (2005). Note other work has indicated a small and insignificant impact of house prices on consumption (Calomiris et al. (2009)).

[13] Invitation Homes notes in the Social Responsibility section of its website that one of its contributions to the communities in which it invests is 'the company paid approximately $306 million in state and local taxes; money that was invested back into local schools, roads, and social services.'

existing owners, and can promote creation of local businesses (Glaeser et al. (2018)). However, gentrification may also displace low-income renters, resulting in less economically diverse neighborhoods (Couture et al. (2019) and Berkes and Gaetani (2022)). Diamond and McQuade (2019) finds that provision of tax credits to finance low-income housing in low-income neighborhoods results in increased house prices and attracts racially and income diverse populations. Hwang and Lin (2016) summarizes many factors that have been proposed as contributing to gentrification, but note that little is known about what initially triggers gentrification. To my knowledge, my paper is the first to examine whether institutional investment in residential property impacts housing quality and neighborhood demographic composition.

III. Theoretical Framework

A. A Two-House Model

I develop a Bertrand-style model of rent and quality competition in which home improvements increase neighborhood quality. Consider a neighborhood in which there are two identical houses, 1 and 2. Each house is rented for a price $r_i \in [0, \infty)$ with $i \in \{1, 2\}$, and the quality of each house, s_i, may be improved for a cost $c_i = s_i^2/2$. The quality of houses within a neighborhood determines the overall neighborhood quality, n. Assume that neighborhood quality is given by:

$$n = \alpha(s_1 + s_2) \tag{1}$$

with $\alpha \in (0, 1)$. Renters have identical (indirect) utility functions in which their utility is increasing in both the quality of the house they rent and the overall neighborhood quality[14]:

$$U = \theta(s_i + n) - r \tag{2}$$

[14] Potential renters obtain zero utility if they do not rent at all.

where $\theta \in (\underline{\theta}, \bar{\theta})$ is a parameter that expresses each renter's preference for quality. I assume that taste for quality is uniformly distributed in the economy according with unit density. The higher the quality of rental housing and surrounding neighborhood, the higher utility U enjoyed by the renter for any given price r. Hence, renters with a higher θ will be willing to pay more for higher quality housing.

If only one quality, s, is offered at a rental price r, the demand for rental housing is the number of consumers with the taste parameter θ such that $\theta(1+2\alpha)s \geq r$. Hence, demand is $D(r) = N[\bar{\theta} - (r/(1+2\alpha)s)]$ where N is the total number of potential renters.

If there is more than one quality of rental housing offered, the potential renters choose among these qualities as well as choosing whether to rent at all. Denoting the high quality house by index 1 and the low quality house by index 2, the demand schedules for each landlord are as follows. The demand for the high quality house is:

$$D_1(r_1, r_2, s_1, s_2) = \begin{cases} \bar{\theta} - \frac{r_1}{s_1+\alpha(s_1+s_2)} & \text{if } r_1 < \frac{s_1+\alpha(s_1+s_2)}{s_2+\alpha(s_1+s_2)} r_2 \\ \bar{\theta} - \frac{r_1 - r_2}{s_1 - s_2} & \text{if } \frac{s_1+\alpha(s_1+s_2)}{s_2+\alpha(s_1+s_2)} r_2 \leq r_1 \leq r_2 + \bar{\theta}(s_1 - s_2) \\ 0 & \text{if } r_1 > r_2 + \bar{\theta}(s_1 - s_2) \end{cases} \tag{3}$$

and demand for the low quality house is given by

$$D_2(r_1, r_2, s_1, s_2) = \begin{cases} \bar{\theta} - \frac{r_2}{s_2+\alpha(s_1+s_2)} & \text{if } r_2 < r_1 - \bar{\theta}(s_1 - s_2) \\ \frac{r_1 - r_2}{s_1 - s_2} - \frac{r_2}{s_2+\alpha(s_1+s_2)} & \text{if } r_1 - \bar{\theta}(s_1 - s_2) \leq r_2 \leq r_1 \frac{s_2+\alpha(s_1+s_2)}{s_1+\alpha(s_1+s_2)} \\ 0 & \text{if } r_2 > r_1 \frac{s_2+\alpha(s_1+s_2)}{s_1+\alpha(s_1+s_2)} \end{cases} \tag{4}$$

Suppose that the two houses are owned by two different investors, A and B. To facilitate analysis, let the game be conducted in two stages. In the first stage, the landlords simultaneously decide whether or not to make improvements to their house. In the second stage of the game, each investor sets their rental price. At this stage, the costs of any quality improvements are already sunk. I obtain a sub-game perfect Nash equilibrium of the game using backwards induction. I show the best response functions for each landlord in Appendix Appendix .A.

I find the equilibrium prices are rents are higher for both quality profits than in the case where there is no positive externalities from home improvements for the other renter in the neighborhood. Although quality for the high quality house is increasing in the degree of spillover from home improvements to neighborhood quality, the quality of the low quality house is decreasing in the degree of this spillover. Hence, where there are positive externalities from home improvements to neighborhood quality, there is more diversity in the quality of housing offered. Profits for both the high quality and low quality landlord are increasing in the degree of spillover from home improvements. However, the competition between landlords ensures that they are not able to extract all surplus from renters. Instead, the utility of the high and low quality house renters is increasing in neighborhood spillovers, even with higher rent and lower quality being offered to the renter of the low quality house (i.e. the benefits from neighborhood improvement more than compensate the renter for the marginal reduction in own-house quality). Figure 9 charts these key results for different degrees of spillover from home improvements to neighborhood quality.

Next I consider the impact of a merger between the two landlords. I show the merged landlord chooses to offer one quality of housing at a quality that is only slightly less than the high quality house in the competitive case. Hence, the neighborhood quality (measured as the sum of the quality of individual houses) is significantly higher following a merger. Increased concentration of ownership allows the merged landlord to fully internalize the benefit of neighborhood improvements, so they offer higher quality housing at higher prices.

Finally, I consider the inclusion of an owner occupier in the neighborhood. I find that increased rent prices relax the borrowing constraint for the owner occupier, allowing her to make more improvements to her house. These improvements have a positive externality on neighborhood quality that enables the landlord to free ride off of the improvements made by the owner occupier. I provide full derivation of these results in Appendix Appendix .A.

My model generates the following empirical predictions about the effect of institutional mergers on neighborhoods:

Hypothesis 1 Following an institutional merger, rent and house prices will increase in neighborhoods where both the acquirer and target owned properties.

Hypothesis 2 Quality of rental housing will be higher following an institutional merger in neighborhoods in which both the acquirer and target owned properties.

Hypothesis 3 Owner occupiers will make more home improvements to their properties in neighborhoods in which both the target and acquirer owned properties following an institutional merger.

IV. Data and Investor Classification

My core analysis relies on the complete ownership, transaction, and valuation history for all residential properties in fifteen counties of Atlanta, GA from 2010-2021. These counties include DeKalb and Fulton counties (that absorb the City of Atlanta) and the surrounding counties: Gwinnett, Cobb, Paulding, Douglas, Fayette, Coweta, Henry, Walton, Forsyth, Cherokee, Clayton, Bartow, Newton, and Rockdale. These counties collectively hold 6.9 million inhabitants. My data is compiled from FOIA requests made to Tax Assessor Office records supplemented with City of Atlanta permitting records and ownership records from OpenCorporates. In addition, I rely on multiple auxiliary datasets to control for economic and real estate trends within neighbourhoods and assess the robustness of my core findings. I provide a brief overview of the different data sources below.

In order to proceed clearly, I introduce some terminology to clarify the rest of the paper. I define "property" as an individual housing unit that includes a "dwelling" defined as any structural features and the land on which the dwelling is situated. Following Reher (2021), I define "quality" as a structural feature of the dwelling. I use the term "improvement" to refer generally to an increase in quality, encompassing both large structural changes to the dwelling (e.g. addition of another room) as well as smaller improvements (e.g. replacement of driveway).

A. Description of Datasets

I use and combine the following datasets in my paper:

County Tax Assessor Records

This dataset contains all property-level information on ownership and appraisal values from 2010-2021. Tax Assessors are required to keep records of the ownership status of all properties including owner name and owner address. In addition, tax assessors provide annual valuations for tax purposes including total assessed value, total appraised value, land appraisal and improvements appraisal. This information is supplemented with basic property characteristics including location, neighbourhood, lot area and shape. Some counties include historical sale prices and an assessment of the quality of the unit in this data.

I supplement my primary analysis with details of tax appeals. [15] This data specifies the property against which an appeal was lodged, the date of the appeal, and the grounds for the appeal. The data may also include the taxpayer's asserted property value, whether the tax payer provided evidence to justify their valuation, the board of assessors' assessed property value, and the property valuation following resolution of the appeal.

OpenCorporates

OpenCorporates maintains a database of over 200 million companies globally. The database contains information on the company's registered address (as recorded in the state or national company register), jurisdiction, its incorporation date, the company's agent and its address, and any directors or officers. It also links companies within its directory by corporate group, listing relevant parent or subsidiary companies. This is the primary database I use to match a private limited liability company (LLC) to its corporate parent.

Permit Data

[15] Two counties (Paulding and Douglas) provided me with the universe of tax assessor data. This includes over 70 different databases, some with over 150 variables, across hundreds of thousands of observations annually. These databases include information on all taxable items within the county, including commercial land and improvements, taxable accessories, aircraft, boats, fireplaces, etc. Details of the information available in the Tax Assessor records are available in the WinGAP Technical Workshop summary.

The City of Atlanta maintains an online portal containing all permits applied for from 2010-present. Each permit is sorted into a category based on the nature of the works to be completed. The relevant categories for my study are:residential addition; residential alteration; residential conversion; residential miscellaneous non-structural; residential miscellaneous structural; residential pool; residential repair. [16] Each permit application contains the date of application, the address of the building, the name of the applicant [17], the status of the application, and a description of the works involved. Hence, each permit can be described by the category of works (as above) or by the description of the works.[18] Hence, the nature of the works is able to be coded using both the existing categories and textual analysis of the work described. City of Atlanta permit data is combined with permit data provided by Paulding County and Douglas County Tax Assessor offices.

Zillow

Zillow produces comprehensive indices of house prices and rental rates by zipcode. To measure rents, I use the Zillow Observed Rent Index (ZORI). This index measures the monthly rent for each zipcode in the units of nominal dollars per month. The ZORI imputes changes in rent over time by calculating the price difference for the same unit listed over time, then aggregating those differences across all properties repeatedly listed on Zillow. This allows the index to control for changes in the quality of the available rental stock through time, so it is not bias by the current composition (unlike pure repeat-listing indices). This index is available from 2014-present.

To measure house prices, I use the Zillow Home Value Index (ZHVI). This index is built from monthly estimates of property-level valuations calculated by Zillow ('Zestimates'). Importantly for this study, the ZHVI corrects for appreciation from home improvements, so changes in the quality of the housing stock are not reflected in the

[16] Future versions of this paper may include Residential Demolition and Residential New permits but at this stage my study is primarily concerned with short term changes to existing structures rather than new development.

[17] The application will often be a commercial owner or the contractor completing the works. For example, "Kuhlemann Alterations".

[18] A typical residential alteration may be described as "a new covered porch, new exterior bath and new terrace" whereas a typical residential non-structural permit may be for a "new fence in front yard" or "replacing driveway, walkway, and patio in same footing 17000 sq ft.".

appreciation rate of the neighbourhood. This index is available for the full length of my sample 2010-present.

Home Mortgage Disclosure Act (HMDA)

The HMDA requires the collection and publication of data on the vast majority of home mortgage applications and loan approvals in the United States. This includes first mortgages as well as refinances. The data include each application's status,loan amount, the purpose of borrowing, the occupancy type, as well as key demographic information about the borrower (income, race, and ethnicity).

I filter the HMDA data to retain applications that satisfy the following conditions: property type = 1 (1 -4 family home) and loan type = 1 (conventional loans). I additionally require that the applications have a non-empty census tract number, and that they were not flagged for data quality issues (edit status = "NA"). I examine all applications that satisfy the stated criteria as well the subset of those loans that are identified as originated (action taken = 1). I further split the sample into applications for the purpose of home purchase (loan type =1) and those for the purpose of home improvements (loan type =2). For some specifications, I use occupancy type to distinguish between investors and owner occupiers. [19]

I assign a race and ethnicity to each application by the following process. If there is one applicant listed on the application, the application is classified according to the race/ethnicity of that individual. If the individual identifies as being of more than one race/ethnic background, I identify the application as 'mixed race'/'mixed ethnic heritage'. If there is more than one person listed on the application, the application is classified according to the race/ethnicity of both parties (if both parties identify as being of the same race) or mixed race/ethnic heritage (if the parties identify as being of different races or are mixed race). I also generate a broad category of all applications that are not classified as being non-Latino/Hispanic white.

[19] It is important to note the limitations of this data. Occupancy status is prone to misreporting. Elul et al. (2019) and Fisher and Lambie-Hanson (2012) find that residential real estate investors often misrepresent their status as owner-occupiers to obtain a lower mortgage rate. For this reason, analysis of investor loans should be viewed as representing the minimum response of investors to treatment.

I obtain census-tract level population and median family income from the Federal Financial Institutions Examination Council's census data. This data also contains the total number of 1-4 family units, and the number of owner-occupied units that act as controls in some regression specifications.

American Community Survey Data

I obtain age, unemployment level, education level, race, median income, labor-force participation rates, and insurance/social security details from the American Community Survey (ACS) 5-Year Estimates provided by the US Census Bureau. ACS Census data is available at varying frequency depending on the granularity of the geographic region, with data from smaller geographic areas averaged over time to create more robust estimates. ACS 5-Year estimates represent averages obtained from fives years of data (e.g. 2016-2020) and are available at the census tract level. Census tracts are the smallest geographic unit available in the ACS and are defined to be between 1,200-8,000 inhabitants with an optimal size of 4,000. Hence, these tracts represent small communities/neighborhoods with the boundaries typically following visible and identifiable geographic features. Although ACS 5-Year estimates cannot be used to provide a single year 'snapshot' of neighborhood composition, they can be used to track demographic changes through time.

B. Descriptive Statistics

B.1. Data Construction

I start with the annual Tax Assessor records from 2010-2021. I generate a time series of ownership and valuation by matching properties on Parcel ID number. I drop any records for which there is no Parcel ID and any records for which there is no numbered address.

I classify all properties in which the owner's address matches the property address as being owner-occupied. This may bias the estimate of owner-occupation upwards, as some small property investors may choose to have tax accounts delivered to the rental property, or may choose to use the property address as the owner contact address in order to maintain the perception that the property is owner-occupied for mortgage rate purposes (Elul et al. (2019)). However, it is unlikely to falsely capture large investors that can easily conceal their ownership through a registered agent, if it is desired. To further validate these results, I cross-check my descriptive statistics against ownership estimates from the US Census Bureau. I find that my measure of owner-occupancy is within 5% of the Census-reported level.

For those properties that are not owner-occupied, it is necessary to identify an ultimate owner. First, I identify all owner-contact addresses that are associated with more than 100 properties in the sample. I manually search to match each of these addresses with an ultimate owner, which generates a database of 396 ultimate owners and contact address pairs. This process also generates a list of " false friends": registered agents, lawyers, tax specialists, etc, whose addresses appear multiple times belonging to different LLCs but are not informative as to the ultimate owner.

Second, I utilise OpenCorporates to identify each LLC's registered address, agent name, agent's address, parent company, and parent's address. I use this additional contact information to match additional LLCs to their parent in the ownership database. This process is described in detail in Appendix Appendix .B.

Finally, I assume all properties that have the same owner contact address have the same owner, provided as the owner does not appear in my list of false friends. I verify the robustness of this process by ensuring that no address matches to more 100 properties without having been previously identified in my sample.

I further classify investors according to their total number of unique properties owned over the 12 years of my sample: micro investors are those with only one investment property; small investors are those with between 2-10 investment properties; medium investors are those with between 11-50 properties; large investors are those with over 51 properties.

Tax Assessor records contain the universe of all properties in an area. I focus on the impact of institutional investment on single family rental market. Hence, I include only properties categorised as residential lots ("R3" according to the Tax Digest Consolidated

Summary). I exclude commercial, agricultural, industrial, utilities, conservation, and other properties zoned for specific land-use from my analysis. For counties where I have not been provided with sales data, I need to identify whether a transaction took place via imputation. I specify that a transaction has taken place if the owner name is not a substring of the previous owner name.[20]

C. Identify SFR Investors

Institutional involvement in the SFR market only began within the last 10 years. Other large investors in the residential real estate market act as either property developers or asset flippers that aimed to build/improve a property within a minimal period of time to maximise capital appreciation at sale. Firms involved in this style of real estate investing are typically geographically localized.[21] SFR investors are unique among large investors in that they acquire properties primarily to offer as rental homes.[22] As a result, SFR investors have a longer investment horizon, with their holding period resembling that of very small "mom and pop" investors that own a single rental property (see figure **??**).

Previous approaches used by researchers to identify property investors are of limited use for identifying SFR investors.[23] I propose a hybrid approach to identify SFR investors

[20] I require that the owner name not be a substring of the previous owner name in order to avoid erroneously classifying divorces (where one partner's name is dropped from the owner name) as changes in ownership.

[21] Indeed, no one investor owned more than 1000 properties across the United States prior to 2013.

[22] SFR investors are securitize the properties they invest in using the revenues from the rental income and the underlying properties themselves as collateral. Specifically, SFR securities are typically collateralized by a single loan that is secured by first-priority mortgages on the underlying properties.The securities are is tranched and pay interest to a schedule using the cash generated from the SFR rental properties. Since Invitation Homes' first issuance in 2013, $69.6b in single-borrower issuances has been raised across 113 transactions from 16 sponsors backed by 355,000 SFR properties, according to KBRA's report SFR Securitizations: A Decade in the Making.

[23] For example, one approach use HMDA data to identify investors, but only captures those investors that rely on local credit markets for borrowing (SFR investors typically borrow via securitization) and is prone to misreporting (Elul et al. (2019) and Fisher and Lambie-Hanson (2012)). Ownership tenure may also be used as a proxy for investor activity, with those who own a house for a short time assumed to be investors (e.g. Bayer et al. (2021) and Giacoletti and Westrupp (2017)). But this fails to capture buy-to-let SFR investors that have a significantly longer holding period (see figure **??**). Finally, Lambie-Hanson et al. (2019)use naming heuristics to identify investor type (e.g. classify names that include "LLC", "Corporation", "Partnership"). This approach is effective for identifying institutional investors, but also captures many corporate owners that are not SFR providers (e.g. builders, property developers, banks, etc).

in this paper. First, I compile a list of SFR providers from mortgage securitization issuances and news reports.[24] For US-listed SFR providers, I identify subsidiary names from SEC 10-K Exhibit 21.1. [25] I record subsidiaries by parent-year to capture any changes in ownership due to mergers.[26] However, this approach is only effective for identifying subsidiaries of US-listed SFR providers. To identify the subsidiaries of unlisted SFR providers, I use the database of large investors I compiled using OpenCorporates to identify the ultimate parent. To ensure that I have not missed any entities, I cross-check the addresses identified as belonging to SFR entities in the Florida Divisions of Corporations website. [27] Public data is prone to typos and spelling irregularities so I use the compiled list of addresses to identify any SFR subsidiaries that were erroneously classified due to minor discrepancies in their name. Details of this process are in Appendix B.

D. Mergers in the SFR Market

I use CapitalIQ to identify the largest mergers of institutional investors in the single family rental market. I provide details of the screening process in Appendix Appendix .D. Table 1 summarizes the four mergers that I use for my analysis. All mergers were completed between 2015-2017, which enables me to obtain data for (a minimum of) three years before and after the mergers to analyze. All but one of the SFR investors were publicly traded at the time of the mergers, so I am able to obtain detailed information on the geographic distribution of each portfolio from annual reports. Although Colony American Homes was private at the time of its merger, the combined firm, Colony Starwood, provides a

[24] Many SFR providers borrow via securizations of their mortgage portfolios. This is a unique feature of the SFR business model and allows a clear classification of these firms. However, I supplement these issuances with news reports so as to not exclude entities that are in the business of providing SFR services but do not borrow via securitization in the United States.

[25] For example, Invitation Homes' list of subsidiaries is available here

[26] It is rare for subsidiary names to change with ownership. For example, Invitation Homes reports 'SWAY 2014-1 Borrower LLC' as a subsidiary even though this entity has been absorbed in two large mergers since its creation under Starwood Waypoint.

[27] Florida is unique in enabling search by address rather than solely by corporate name. Hence, it is possible to find all Florida listed subsidiaries associated with a corporate headquarters. Florida has experienced high levels of SFR investment post-GFC so many of the same subsidiaries are active in both Georgia and Florida.

detailed overview of their portfolio pre- and post- acquisition.[28]

V. Empirical Framework

I use the four largest SFR mergers to identify the impact of changes in institutional market share on gentrification. These mergers created discrete jumps in the concentration of institutional ownership within neighbourhoods depending on the degree of overlap between the acquirer and target's Atlanta portfolio. I define a neighborhood as a census tract for all specifications except those that examine house prices and rent for which data is only available at the zip code level.

The degree of overlap between the acquirer and target's portfolio is plausibly independent of local economic conditions, yet it influences the market power of the acquiring landlord. Increasing the market power of a landlord could causally affect local conditions by enabling the landlord to charge higher rent, which would increase house prices (i.e. higher rent mechanically increases the value of houses within a discounted cash flow or discounted dividend valuation framework). Equally, increasing the market share of a landlord could also incentivize the landlord to make greater improvements to their properties if they anticipate that improvements could increase the quality of the neighborhood (with resulting increases in rents and house prices). Construction/improvement works may encourage other homeowners/landlords within the neighborhood to make further investments in their properties (Kuhn et al. (2011)).

I compare property prices and investment within neighborhoods in which both the acquirer and target owned properties to those neighbourhoods where the acquirer already owned at least one property but the target did not. Hence, I can identify the impact of increased concentration of institutional ownership independent from local market conditions that would otherwise influence selection (i.e. institutional investors may be good at picking neighbourhoods where prices or quality are likely to rise). Furthermore, by focussing on mergers that include a national portfolio of institutional properties, I can

[28] Details of Colony Starwood's portfolio pre- and post- merger are available in Colony Starwood's 10K.

minimise the possibility that the portfolio was acquired in order to increase ownership within specific neighbourhoods in Atlanta. I only use as controls those neighborhoods that did not experience a merger at any time during the sample period. Hence, there is no risk that a neighborhood that was treated in one merger would be used as a control for another.

Treatment effects estimated from this DiD specification could be confounded by selection for two reasons. First it could be that the acquirer chooses to acquire the target's portfolio because of market overlap (synergies) between the two portfolios. Indeed, all acquirers state the cost efficiencies of market overlap as one of the benefits of the acquisition.[29] It follows that the acquisition decision may be endogenous to the degree of overlap between the acquirer and the target's portfolios. Although portfolio complementarity may influence the portfolio acquisition decision, the degree of overlap within individual neighborhood in the Atlanta Metro region is unlikely to influence the acquisition decision in the context of a national portfolio (in fact, institutional investors regulatory filings and press releases refer to overlapped "markets" as cities rather than tracts or zips within cities). Even if census tracts (zips) were selected for the degree of overlap, the proposed DiD estimator would still capture the impact of mergers on local prices, but the estimated average treatment would likely be larger than the effect of landlord concentration absent a merger.

Treatment effects could also be confounded due to selection bias because an institutional portfolio is more likely to become the target of an acquisition where there is mis-

[29] For example, the 10 August 2017 press release to announce Invitation Home's merger with Colony Starwood stated "The two companies have very similar portfolios of homes focused on overlapping, strategically selected, high-growth markets...The combined portfolio would also have an average of 4,800 homes per market, allowing it to leverage economies of scale and improve operating efficiency, while also enhancing customer service. " Similarly, an investor presentation released at the time of Starwood Waypoint's acquisition of Colony American highlights the "focused strategy of concentrated market density in attractive, high-growth markets to drive operational efficiency, economies of scale and attractive returns." The presentation goes on an increase of 175 bp in portfolio renewal rent increases in the combined company (Exhibit 99.2 of Form DEFA14A filed 21 September 2015). Finally, American Homes 4 Rent notes that "[g]iven the geographic overlap of American Homes 4 Rent and American Residential Properties portfolios, operational synergies are expected to be achieved by reducing duplicate expenses for internet charges, supervisory property management personnel, management information systems and other back-office functions." (Exhibit 99.1 of 3 December 2015 Form 425 filing)

alignment between the acquirer's and the market's perception of target portfolio value. If the acquirer's acquisition decision depends on its perception of the growth prospects of the markets within target's portfolio, the acquirer may have already purchased property in these markets. Hence, the degree of overlap may be endogenous the acquirer's perception of growth prospects in those markets. If the acquirer is better at picking winners than the market, then a finding that prices rise in areas of high overlap could be simply be market prices catching up with the acquirer's assessment of market outlook. I conduct further tests to evaluate the risk of selection bias in the Appendix.

For comparability with previous work, I start with the traditional differences-in-differences with two-way fixed effects (TWFE) model that estimates:

$$\mathrm{y}_{n,t} = \alpha + \beta_1 \mathrm{Post}_t + \beta_2 \mathrm{Treat}_n + \beta_3 \mathrm{Post}_t \text{ x } \mathrm{Treat}_n + \gamma_{c,t} + \zeta_n + \epsilon_{n,t} \tag{5}$$

$\mathrm{y}_{n,t}$ is the main dependent variable following a merger in neighborhood n, in period t. Post_t is a binary variable that takes the value of 1 for neighbourhood-year observations following a merger. Treat_n indicates treatment for zip z. I include county x year fixed effects, $\gamma_{c,t}$, to control for time-varying characteristics at the county level. Hence, county-level conditions, such as local economic performance and demographics, would not confound the estimated treatment of institutional landlord mergers on local prices. I also include neighborhood fixed effects, ζ_n, to account for fixed (or slow moving) unobservable neighborhood characteristics that may impact local conditions (such as geographic characteristics and climate conditions). Thus, after controlling for these fixed effects, the DiD estimates capture the differences in the dependent variable post-merger across neighborhoods within a county.

Recent research in econometrics has found that this TWFE estimator may be biased when treatment is staggered and the treatment effects are heterogeneous. To address this concern, I follow the approach proposed by Sun and Abraham (2021). They propose an"interaction-weighted" approach for estimating dynamic treatment effects. Specifically, their approach first estimates cohort-specific average treatment effects in a regression with cohort and relative period indicators. These cohort-specific treatment effects are identified under parallel trends and no anticipation assumptions. Average treatment effects can be estimated using weights derived from the sample share of each cohort. To implement this approach, I estimate the following equation:

$$\mathrm{y}_{n,t} = \gamma_{c,t} + \zeta_n + \sum_{g \notin G} \sum_{s \neq -1} \beta_{g,s}(1\{g_n = g\} \cdot D^s_{n,t}) + \epsilon_{n,t} \tag{6}$$

where $\mathrm{y}_{n,t}$ is the main dependent variable following a merger in neighborhood n, in period t. I include county x year fixed effects, $\gamma_{c,t}$, and neighborhood fixed effects, ζ_n. $(1\{g_n = g\}$ is the cohort-indicator representing each cohort, g, and $D^s_{n,t}$ is the relative period s from a merger in neighborhood n in period t. Hence, $\beta_{g,s}$ is the cohort-specific average treatment effect on the treated. The average treatment effect is given by the sample-share weighted average of these cohort-specific estimates. I report this ATT alongside the TWFE estimate in this paper. My results are robust to the use of alternative specifications for staggered treatment designs, such as Callaway and Sant'Anna (2021).

A. Impact of mergers on local prices

For each institutional merger, I estimate the above TWFE equation 5 and staggered difference-in-difference approach in equation 6 for neighbourhood house prices and rental prices. The dependent variables are $ln(\mathrm{HousePrice}_{z,t})$, the log Zillow house price index following a merger in zip z, in period t, and $ln(\mathrm{Rent}_{z,t})$ is the log Zillow rent index following a merger in zip z, in period t.

Table 4 presents the DiD estimates for equations 5 and 6. The estimates show that the DiD estimator is significantly positive for rent and house prices following a merger. This is consistent with landlords raising rent in regions of reduced competition as a result of mergers, and house prices adjusting in neighbourhoods where there is consolidation as a result of the merger. Based on the estimates in Table 4, I find that rent prices are 5.0% higher following the merger in overlapped zip codes than other zip codes. Similarly, house prices are 3.0% higher in zips overlapped zips. These findings are directionally consistent with the previous findings in (Lambie-Hanson et al. (2019),Mills et al. (2019) and Gurun et al. (2022)).

Figure 3 presents the rent difference between zips where the acquirer increased concentration of ownership after the merger and zips where the acquirer owned at least one property prior to the merger. This figure shows no evidence of parallel trends as there is no trend in rent prices between treated and untreated zips in the years preceding the merger transactions. The prolonged consistency in rents between treated and non-treated zips prior to the merger supports the conclusion that the observed increase in rent is driven by the merger rather than other confounding factors. Figure 4 similarly presents the house price difference between zips where the acquirer increased concentration of ownership following a merger and those zips where the acquirer owned at least one property prior to the merger but the target did not. The figure shows very little evidence of a trend in house prices prior to mergers, and a strong increase in house prices subsequent to the merger.

Both figures indicate a lag of approximately one-two years before prices in overlapped zips diverge from non-overlapped zips. This lag can be explained by delays in contract negotiations. Although price indices reflect the current advertised price of properties, acquirers typically have to wait until the end of current leases to renegotiate prices with existing tenants. On observing higher prices from merged landlords, other landlords would then need to wait for an opportunity to renegotiate with their tenants. House prices could then adjust to reflect increased returns to renting.

B. Impact of mergers on house improvements

Prices are only informative about one component of neighborhood welfare. It is possible that the observed price increases for houses and rents are accompanied by improved quality of housing. In fact, institutional investors state that they make improvements to the houses they own, with Invitation Homes estimating it makes improvements of $25,000 on average to each home in its portfolio. According to the model presented in this paper, institutional investors are likely to make the most improvements to properties in areas where they have the highest concentration of ownership because improvements within a concentrated area are more likely to improve neighbourhood quality (with associated increases in rent and house prices).

To test if institutional investors make more improvements to houses within neighbourhoods in which they own a larger share of houses, I estimate the following difference-in-difference model for property-level valuations following each merger:

$$\begin{aligned} ln(\text{Valuation}_{i,n,t}) = \alpha + \beta_1 \text{Post}_t + \beta_2 \text{Treat}_n + \beta_3 \text{Post}_t \text{ x } \text{Treat}_n + \beta_4 \text{Merged Landlord}_{i,t} \\ + \beta_5 \text{Post}_t \text{ x } \text{Merged Landlord}_{i,t} + \beta_6 \text{Treat}_n \text{ x } \text{Merged Landlord}_{i,t} \\ + \beta_7 \text{Post}_t \text{ x } \text{Treat}_n \text{ x } \text{Merged Landlord}_{i,t} + \gamma_{n,t} + \epsilon_{n,t} \quad (7) \end{aligned}$$

$ln(\text{Valuation}_{i,n,t})$ is the County Tax Assessor's valuation of property i in neighbourhood n in period t. Treatment and timing variables are defined similarly to in the price regressions. Post_t is a binary variable that takes the value of 1 for neighbourhood-year observations following a merger. Treat_n indicates treatment for neighbourhood n in a merger. In these regressions, I use census tracts (which are significantly more granular than zips) to define treated neighborhoods. To evaluate the impact of ownership by a merged firm, I introduce the binary variable $\text{Merged Landlord}_{i,t}$ that is equal to 1 if property i is owned by either the acquirer or the target at period t. I include neighbourhood x year fixed effects, $\gamma_{n,t}$, to control for time-varying characteristics at the neighbourhood level. Hence, neighbourhood-level conditions, such as local economic performance and demographics, would not confound the estimated treatment of institutional landlord mergers on local home valuations. After controlling for these fixed effects, the DiD estimates captures the impact of ownership by a merged landlord on property valuations post-merger within each neighbourhood.

Table A1 shows the results of this regression. I find no evidence that valuations for properties owned by merged landlords are significantly higher in regions in which the landlord increased its market share as a result of a merger. Rather, in some specifications, the tax valuations of properties owned by the merged landlord fall in neighborhoods in which the merged landlord increased its share of ownership as a result of the merger. This may suggest that the loss of competitive pressure as a result of mergers overrides any benefit from economies of scale such that institutional investors do not make improvements to properties in neighborhoods where they have a higher market share post-merger. However, further analysis in Panel C of A1 shows that there is no change in the tax assessors' assessment of the condition (quality) of properties owned by the merged landlords around mergers. These seemingly contradictory findings could be a consequence of tax valuations not incorporating the value of any improvements made to properties. This would occur if the tax assessor valuations were successfully appealed to minimize the merged landlord's tax obligations. I examine this explanation for reduced valuations in section V.D.

To further isolate the changes in property improvements post merger, I divide merged landlords' properties in acquirer-owned properties and target-owned properties in the following regression:

$$
\begin{aligned}
ln(\text{Valuation}_{i,n,t}) = \alpha + \beta_1\text{Post}_t + \beta_2\text{Treat}_n + \beta_3\text{Post}_t \text{ x } \text{Treat}_n + \beta_4\text{Acquirer}_{i,t} \\
+ \beta_5\text{Post}_t \text{ x } \text{Acquirer}_{i,t} + \beta_6\text{Treat}_n \text{ x } \text{Acquirer}_{i,t} + \beta_7\text{Post}_t \text{ x } \text{Treat}_n \text{ x } \text{Acquirer}_{i,t} \\
+ \beta_8\text{Target}_{i,t} + \beta_9\text{Post}_t \text{ x } \text{Target}_{i,t} + \beta_10\text{Treat}_n \text{ x } \text{Target}_{i,t} + \beta_11\text{Post}_t \text{ x } \text{Treat}_n \text{ x } \text{Target}_{i,t} \\
+ \gamma_t + \epsilon_{n,t} \quad (8)
\end{aligned}
$$

Table A3 in the Appendix presents the results from this regression. It shows that the valuation of acquirer-backed properties significantly decreases following the merger. If we believe tax valuations are informative, this result is consistent with the finding that there is no evidence that acquirer's make more improvements to properties in neighborhoods in which they have a higher concentration of ownership.

B.1. Permitting Activity

Since tax assessors valuations are prone to appeals, they may not be sensitive to changes in housing quality. Therefore, to better understand changes in the quality of housing in a neighborhood following an institutional merger, I examine applications for home improvement permits. Permits are required for any home improvements that make structural modifications to a property. Such changes could include the addition of a pool, another bedroom, a resurfaced driveway or roof, or a new fence. However, permits are not required for cosmetic changes even if significant (e.g. entire kitchen or bathroom refits or painting the entire house), so this analysis represents a low estimate of the quality changes that take place in a neighborhood following an institutional merger.

To estimate the impact of increased concentration of institutional ownership on housing quality, I estimate the above TWFE equation 5 and staggered difference-in-difference approach in equation 6 for permits, where $\text{Permits}_{g,n,t}$ is the count of permits issued to group g around mergers in neighborhood (census tract) n, in period t. I also include time-varying neighborhood controls $\text{C}_{n,t}$ including number of one-to-four family homes (to account for changes in home supply), lag house prices, total number of mortgage applications (originations), population, and lagged investor approvals (to control for changes in rental supply). I cluster standard errors at the neighborhood (census tract) level.

Table 6 summarizes the results of these regressions. Further tables showing the full set of regression results including all controls are available in the Appendix Appendix .G. I find that owner occupiers apply for 79% more permits and small investors apply for 47% more permits in neighborhoods that experienced an increase in concentration of institutional ownership following a merger. There is no change in the permitting activity of either larger investors or institutional SFR investors.

For owner occupiers, the increase in permitting is consistent with a wealth effect where rising house prices following the merger enable households to borrow more to make improvements to their homes. For small investors ('mom and pop' landlords) this is suggestive of a change in competitive pressures in the neighborhood. As the model proposed in this paper implies, it is beneficial for landlords to offer different quality properties in order to minimize competitive pressures. The finding that small investors increase their permitting activity when SFR investors do not implies that small investors may aim to offer 'high quality' rental properties within the neighborhood. This suggests that it is smaller landlords that are changing the quality composition of rental property which may limit the supply of affordable rentals to existing/future tenants.

B.2. Loans for Home Improvements

One of the shortcomings of permits is that they are only required for specific structural changes to a property. For example, installation of a pool, a deck, or addition of a new room, would require a permit, but cosmetic changes (including to household fixtures) would not.[30] For this reason, permit data represents a low estimate of all improvements that may be taking place in a neighborhood at a given time. I supplement the analysis of permits with an analysis of loans for home improvements. [31] I disaggregate improvement data by borrower type (owner occupier or self-reported investor) to explore differences in home improvements between owner types. [32]

I estimate the above TWFE equation 5 and staggered difference-in-difference approach in equation 6 for home improvement loan applications and loan originations. $\text{Applications}_{g,n,t}$ is the count of applications by owner type g around a merger in neighborhood (census tract) n in period t. Similarly, $\text{Originations}_{g,n,t}$) is the count of loan originations by group g around a merger in neighborhood n in period t. I also include time-varying neighborhood controls $\text{C}_{n,t}$ including number of one-to-four family homes (to account for changes in home supply), lag house prices, median income, and lagged investor approvals (to control for changes in rental supply) in some specifications. I cluster standard errors at the neighborhood (census tract) level.

Table 5 presents summary results from these regressions. Further tables showing the full set of regression results including all controls are available in the Appendix Appendix .G. I find that the value of all home improvements loans (both applications and approvals) increases following an institutional merger. When I disaggregate by owner type, I find that this effect is due to owner occupiers rather than investors. Owner occupiers increase the value of their applications by between 20-37% in the four years following an institutional

[30] For example, a extensively renovated kitchen with all new appliances and cabinetry would not require a permit unless structural changes were made.

[31] HMDA data splits loan applications by loan purpose so I am able to consider loans for home improvements separately to loans for other purposes (purchase or refinancing).

[32] SFR investors borrow via securitization so investors in this context are small investors who do borrow in local credit markets.

merger in the neighborhood. Increased loans for home improvements could be a result of a relaxation of the borrowing constraint for owner occupiers who are able to obtain higher credit to make improvements to their houses, potentially due to house prices increases following the merger. This finding is consistent with the previous literature that has found higher house prices correlate with increased borrowing as a result of collateral effects (Cloyne et al. (2019)).

However, there is no significant change in the value of loans applied for or approved by investors. This is suggestive that small investors do not borrow to make improvements to their properties in order to compete more effectively with institutional owners.

Hence, both the permitting and home loan data suggests that it is owner occupiers rather than investors that make improvements to housing quality following institutional mergers. To the extent that visible home improvements induce home improvements by one's neighbors (Kuhn et al. (2011)) it appears that it is owner occupiers that influence changes in housing quality rather than housing investors.

C. Neighborhood Composition

I explore the impact of increased institutional ownership on neighborhood composition using using HMDA data. HMDA data can be split into two samples: (1) applications for loans and (2) loan originations. Loan applications indicate preferences/demand for a particular neighborhood whereas loan originations indicate realized movement into a neighborhood. Hence, loan applications and originations are separately informative as to perceived desirability and observed changes within neighborhoods. For each institutional merger, I estimate the above TWFE equation 5 and staggered difference-in-difference approach in equation 6 for mortgage applications and originations.

$\text{Applications}_{g,n,t}$) is the count of applications by group g around a merger in neighborhood (census tract) n in period t. Similarly, $\text{Originations}_{g,n,t}$) is the count of loan originations by group g around a merger in neighborhood n in period t. I also include time-varying neighborhood controls $\text{C}_{n,t}$ including number of one-to-four family homes (to account for changes in home supply), lag house prices, total number of mortgage applications (originations), population, and lagged investor approvals (to control for changes in rental supply). I cluster standard errors at the neighborhood (census tract) level.

Table 8 presents a summary of the regressions for loan applications by racial/ethnic group. Similarly, Table **??** presents a summary of the regressions for loan originations by racial/ethnic group within a neighborhood. Both applications and approvals indicate that neighborhoods are becoming more diverse following institutional mergers. Loan applications (originations) by Black/African Americans are higher by 2.84 (1.35) in neighborhoods in which there was a large increase in concentration following a merger. This corresponds to an application (origination) rate that is 17.9%(15.4%) higher on average relative to neighborhoods that did not experience a large increase in concentration after an institutional merger. Applications (originations) by Latino/Hispanic people are higher by 1.51 (0.86) which corresponds to an application (origination) rate 23.4% (20.8%) higher in neighborhoods that experienced a large increase in concentration as a result of an institutional merger. These findings are robust to the inclusion of a number of controls for housing supply, changes in rental supply, house prices, etc. A careful examination of pre-trends contained in Figure 7 and Figure 8 reveals that there is a pre-trend in applications in the three years prior to the merger. Three years prior to the merger, loan applications/originations are lower in merged neighborhoods for most non-white groups. This can be explained by the timing of the mergers with respect to the Great Recession (three years prior to merger is 2013 for two of the mergers). Institutional investors had only just entered the market and were predominantly buying in high foreclosure neighborhoods. Hence, the finding that there was depressed demand in neighborhoods that would later go on have overlap between institutional portfolios is not surprising: this was precisely what made these neighborhoods so attractive for institutional investment. What is crucial for this study is that increased institutional investment has not dampened demand by minorities. In fact, these trends have continued in the post-merger period.

This increase in demand for properties in merged neighborhoods from Black and Latino/Hispanic applicants corresponds with a decline in demand from white and mixed race applicants. Applications (originations) by non-Hispanic/Latino white people are lower by 2.6 (2.1) in neighborhoods that experienced a large increase in concentration of institutional ownership following a merger. This corresponds to an application (origination) rate that is 6.7% (8.0%) lower in neighborhoods that experienced a large increase in concentration of institutional ownership following a merger. Similarly, mixed race/ethnicity applications (originations) are lower by 0.42 (0.37) in neighborhoods that experienced a large increase in concentration of institutional ownership as a result of a merger. This corresponds to an application (origination) rate that is 21% (28%) lower than in neighborhoods that did not experience an increase in concentration of institutional ownership.

One possible explanation for the increased desirability among people of colour for neighborhoods in which there is a higher concentration of institutional ownership is that institutional investment increases the supply of rental housing.[33] In Atlanta, 52% of households that rent are Black/African American (whereas the total share of Black households in Atlanta is only 37.5% so Blacks are disproportionately represented among renters).[34] For this reason, an increase in rental housing may enable an increase in the number of Black households in a neighborhood. Increased diversity within a neighborhood may make neighborhoods relatively more attractive for POC to purchase housing all else equal. Coefficients from regressions incorporating the lag of investor mortgage originations (as a proxy for rental property growth) are indicative of this. Black/African American applications have a positive and significant correlation with increased investor purchases whereas white applicants have a negative and significant relationship with such purchases.

D. *Tax Assessor Appeals by Investor Type*

Finally, I explore the impact of institutional ownership on local tax revenues. Local taxes are charged on the basis of tax assessor house valuations. Hence, one reason we

[33] I observe this in my data and this is also consistent with the finding of Lambie-Hanson et al. (2019) that owner occupancy falls in neighborhoods that have higher investor activity.
[34] This data is available from the Atlanta Regional Council.

may observe lower home valuations in institutional-owned properties is if institutional investors appeal valuations more than other owner types in order to minimise their tax obligations. I test this hypothesis by running the following regression:

$$Appeal_{i,t} = \alpha + Type_{i,t} + \zeta_{n,t} + \gamma_t + \epsilon_{i,t} \tag{9}$$

where $Appeal_{i,t}$ is the incidence of an appeal by property i in year t. $Type_{i,t}$ is the type of owner, which is delineated into the familiar categories: owner-occupier, tiny investor (1 investment property), small investor (between 1 and 10 investment properties), medium investor (between 10-50 investment properties), large investor (more than 50 properties), and institutional investor. In some specifications I include neighbourhood (tract) x time fixed effects, $\zeta_{n,t}$.[35] Standard errors are clustered at the property level.

Table 9 presents the results of these regressions. I find that institutional ownership is highly correlated with appeals. Indeed, the probability of an institutional investor appealing a valuation is 16.8%, which is higher than any other investor type. This finding is robust to the inclusion of tract x year fixed effects that control for changes in underlying neighbourhood quality and different tax assessors. I find that the probability of an appeal is increasing in the logarithm of the tax assessor's valuation of the property, so appeals tend to be launched where the value of the underlying property is higher.

I find all investor types are more likely than owner-occupiers to appeal their property's valuation. I present these probabilities from the baseline regression in (1) in Table 10. I find that the probability of an appeal is increasing in investor size, even once underlying characteristics of the neighborhood and property values are controlled for. This suggests that larger investors may be more active in trying to minimise their tax obligations. This also implies that there may be economies of scale in efficiently mounting tax appeals.

A high appeal frequency does not imply that these appeals were aimed at reducing the taxable value of the property. Hence, in the subsequent analysis I restrict the data to

[35] For robustness, I also use county (rather than tract) fixed effects. These account for differences between tax assessors and are fully absorbed at the more discrete neighbourhood level. There is qualitatively no difference in the analysis.

appeals on the basis of valuation. [36] I choose to focus on appeals on the basis of valuation for two reasons. First, I am interested in studying how institutional investment impacts the communities in which it occurs. One of the channels through which institutional investors purport to add value to communities is through the payment of local taxes.[37] Hence, appeals against taxable valuations are directly relevant to the community impact of these investors. Second, the data does not specify whether an appeal is "successful" or not. The data only reports the final valuation settled upon during the appeals process. Hence, only appeals on the grounds of valuation can be classified unambiguously as successful or not using this output.[38]

In Table 11, I present the results from the following regression:

$$Success_{i,t} = \alpha + Type_{i,t} + \zeta_{n,t} + \epsilon_{i,t} \tag{10}$$

where $Success_{i,t}$ is a binary variable that equals 1 if the final valuation of property i in year t is less than the board of assessors' valuation for that property in that year. $Type_{i,t}$ is the type of owner, which is delineated into the familiar categories: owner-occupier, tiny investor (1 investment property), small investor (between 1 and 10 investment properties), medium investor (between 10-50 investment properties), large investor (more than 50 properties), and institutional investor. In some specifications I include neighbourhood (tract) x year fixed effects, $\zeta_{n,t}$. Standard errors are clustered at the property level.

I find that all investor types except tiny investors (those with only one investment property) have a higher probability of a successful appeal than owner occupiers. This result is even stronger once I consider the inclusion of evidence in the appeal and the valuation of the underlying property. Institutional investors have a similar probability of success to small investors, and a lower probability than medium and large investors.

[36] Other grounds for appeal include the uniformity of the property, the taxability of the property, the denial of a tax exemption to the property, a taxpayer breach of a covenant on the property, and the denial of a covenant to the property.

[37] For example, Invitation Homes refers to the local taxes it paid as an example of its positive impact on the communities in which it operates.

[38] Although a successful appeal on the basis of one of the other grounds may result in a reduced valuation, it is not clear that this was the primary objective of the appeal and hence we cannot classify such appeals as successful or otherwise purely on the basis of the final valuation.

This result is consistent with the different investment strategies across investor types. Medium and large investors hold their properties for a much shorter period than smaller (or institutional) investors. This is consistent with a "buy to sell" investment strategy that may see these investors may develop (or make improvements to) properties with the intention of selling them immediately following completion of the works.[39] Properties that have been developed or undergone significant change are more difficult to assign a market value to due to a limited transaction history of properties of a similar age or with similar characteristics. This could explain the relative success of appeals from these investor types over other owner types.

Table 12 quantifies the reduction in taxable valuation of successful appeals by investor type. It presents the results from the following regression:

$$AppealSize_{i,t} = \alpha + Type_{i,t} + \zeta_{n,t} + \epsilon_{i,t} \tag{11}$$

where $AppealSize_{i,t}$ is either unscaled or scaled. In the unscaled regression, $AppealSize_{i,t}$ is defined as (1 plus) the logarithm of the difference between the board of assessors' valuation and the final valuation resolved upon as a result of the appeal. The scaled regression defines $AppealSize_{i,t}$ as the difference between the board of assessors valuation and the final valuation divided by the difference between the board of assessors' valuation and the valuation asserted by the taxpayer. Hence, the scaled regression measures the degree of success of the appeal, i.e. the proportion of the difference between the taxpayer's assert value and the board of assessor's value that the taxpayer recovered as a result of the appeal. $Type_{i,t}$ is the type of owner, which is delineated into the familiar categories: owner-occupier, tiny investor (1 investment property), small investor (between 1 and 10 investment properties), medium investor (between 10-50 investment properties), large investor (more than 50 properties), and institutional investor. In some specifications I include neighbourhood (tract) x year fixed effects, $\zeta_{n,t}$. Standard errors are clustered at the property level.

In the unscaled regression, I find that smaller investors experience significantly larger

[39] A low holding period would also be consistent with house flipping.

reductions in property valuations as a result of successful appeals than owner occupiers. Conversely, larger investors and institutional owners experience significantly smaller reductions in valuations than owner occupiers as a result of successful appeals. This could be due to the frequency of appeals: smaller investors appeal less frequently so may obtain larger reductions (if we assume that valuations become additively misaligned over time).

It could be that tax assessors impose unfairly high valuations on institutional owners' properties in order to extract greater tax revenue from them. If that were the case, tax appeals could reflect institutional investors aiming to argue their valuations down to a "fair" level. To evaluate the economic significance of these appeals, I compare the sale price of properties to the tax valuation in the following regression:

$$\text{Valuation Difference}_{i,t} = \alpha + Type_{i,t} + \zeta_{n,t} + C_{i,t} + \epsilon_{i,t} \tag{12}$$

where Valuation $\text{Difference}_{i,t}$ is equal to the sale price of property i in period t minus the tax valuation of property i in period $t-1$. $\text{Type}_{i,t}$ indicates the owner type (as detailed in the above specifications). I include neighborhood x year fixed effects ($\zeta_{n,t}$) and controls $C_{i,t}$ for the number of previous appeals in the regressions. I cluster errors at the property level.

Table 13 presents the results of these regressions. I find a large and significant difference between the valuation difference for institutional investors and owner occupiers. In particular, the valuation difference for institutional investors is over four times higher than that of owner occupiers. Assuming a tax rate of 1% and the median house price of institutional investors in the sample, this implies tax savings of $747 per house per year. Across 280,000 institutional properties in the United States, this represents tax savings of over $209m per annum or $4.1b when capitalised with a 5% discount rate.

VI. Conclusion

This paper examines the impact of increased concentration of institutional ownership of residential housing on neighborhoods. I use a series of national mergers to examine three channels through which institutional ownership may affect communities. First, I directionally confirm previous findings that increased concentration of institutional ownership is associated with higher house and rental prices. I find house prices increase by 6.0% and rental prices by 3.5% in the three years following an institutional merger in neighborhoods that experience a large change in concentration of institutional ownership as a result of a merger.

Higher house and rental prices relax households' borrowing constraint that induces greater spending on home improvements by owner occupiers and small investors. I find that owner occupiers and small investors apply for more permits for home improvement and higher value loans for home improvement in the years following an institutional merger in their neighborhood. In the four years following a merger, owner occupiers are issued with 78% more permits and apply for home improvement loans that are 54% higher in value in neighborhoods in which there was a change in concentration of ownership as a result of an institutional merger. Investors that own less than 10 properties ('small' investors) have a similar increase in permitting activity with 47% more permits issued to small investors in neighborhoods that experience an increase in concentration of institutional ownership.

There is no evidence that institutional investors make more home improvements to properties in areas in which they have an increased market share as a result of a merger. In fact, property valuations for houses owned by the merged landlord are lower in areas in which they gain a larger market share following a merger. I rationalize this finding through forensic examination of tax appeals. I find institutional investors appeal property valuations with a frequency of 16.8% (over 18 times the rate at which owner occupiers appeal). Tax appeals by institutional investors are more successful at reducing the property valuation than appeals by owner occupiers. Once I control for the difference between the tax assessor and owner valuations, there is no difference in the size of the reduction in property valuation obtained as a result of a successful appeal across owner types. These appeals are economically significant. Assuming a property tax rate of 1% and the median difference between tax and realized (sale) valuation, institutional investors are saving \$4.1b through tax appeals. This finding suggests that tax minimization may be another source of value-add pursued by private equity backed companies.

Increased institutional ownership correlates with greater racial and socio-economic diversity in neighborhoods. High house prices following institutional mergers do not reduce diversity of home loan applications or approvals. Rather, I find that home loan applications and approvals for people of color increase in neighborhoods in which there is a greater concentration of institutional ownership following a merger. One potential reason for this is that higher rent prices following a merger may create a greater supply of rental housing. In Atlanta, a large share of rental housing is used by people of color, so a greater supply of rental housing may encourage greater neighborhood diversity. Increased diversity may be a factor that makes a neighborhood more attractive when purchasing a home, especially for minority communities.

To conclude, this paper finds that increased concentration of institutional ownership has nuanced effect on communities. Although it is correlated with increased prices, it seems to generate greater improvements to housing quality, both in rental and owner-occupied homes. Crucially, I find no evidence that increased concentration of ownership results in less diverse neighborhoods. One caveat to this analysis is that Atlanta is one of the areas in the country that has seen the highest levels of institutional ownership, so there are questions as to whether we would observe the same effects in areas where institutional ownership is lower or more dispersed. Further work will examine a national sample to test the external validity of these findings.

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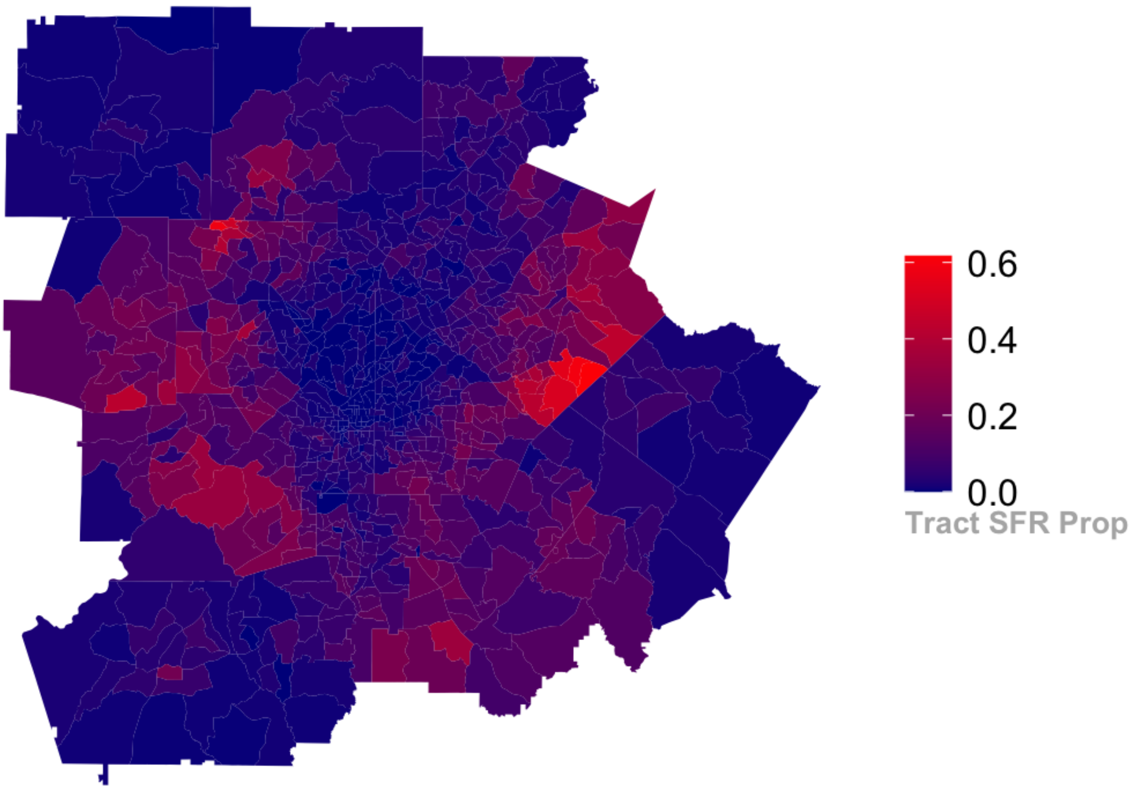


Figure 1: Proportion of Institutional Investor Ownership of Rental Housing by Census Tract
This figure presents the proportion of institutional investor ownership of rental housing by census tract in 2019. It shows that institutional owners have a significant proportion of the overall rental market in many census tracts. Hence, even though institutional owners may have a relatively small share of the single family home ownership market, the significant ownership of rental housing may give them market power in the rental segment.

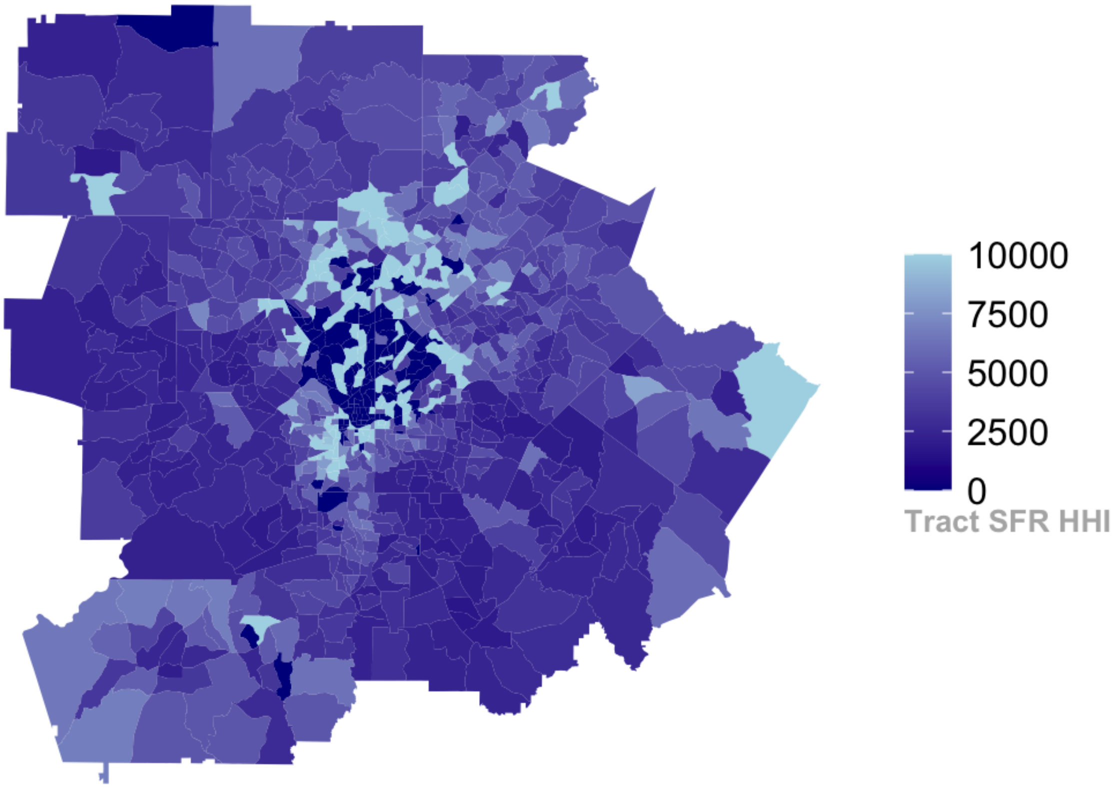


Figure 2: Institutional Investor HHI
This figure presents a Herfindahl-Hirschman Index of institutional ownership of rental housing by census tract in 2019. In some census tracts (markets) there is a single institutional investor present (monopoly); in others, there is at least two institutional owners competing; and in some there is no institutional ownership. This study compares outcomes in markets where there is at least one institutional owner present.

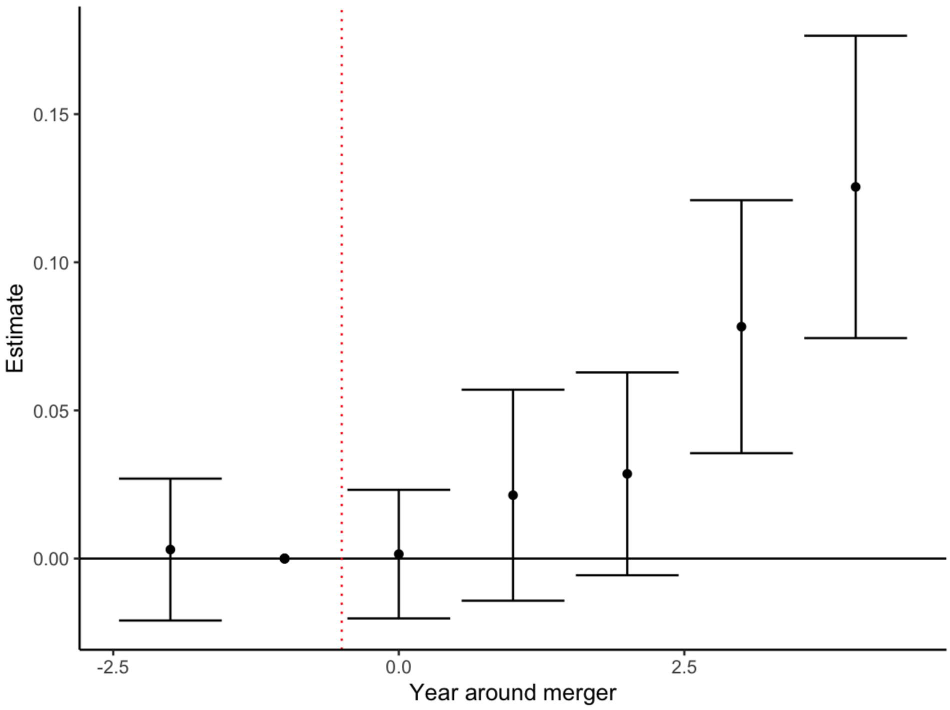


Figure 3: Difference in rent between overlapped and non-overlapped properties around mergers
This figure presents the coefficients from a staggered difference-in-differences regression of the Zillow Rent Index in relation to the mergers. A zip is treated if the acquirer increases its concentration of ownership as a result of the merger. Control zips include all zips in which the acquirer owned at least one property prior to the merger. I include county x year and zip fixed effects in the regression, and cluster standard errors at the zip level. The horizontal axis shows two years prior to the merger until four years after the merger. The vertical access represents the difference between treated and control zips in terms of the natural logarithm of the Zillow Rent Index. Each estimate is presented with 95% error bands.

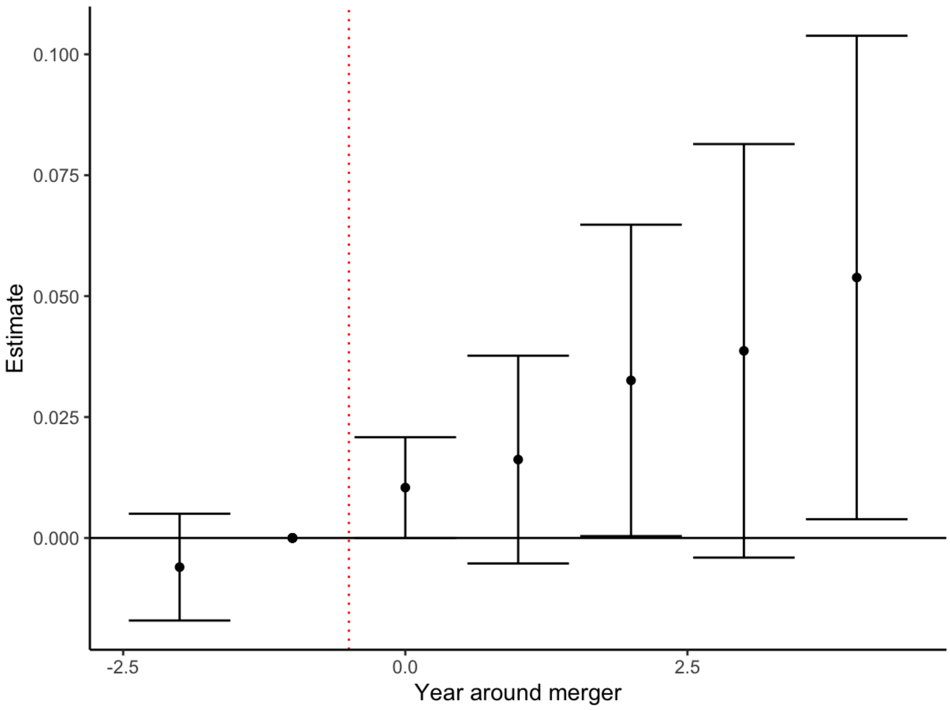
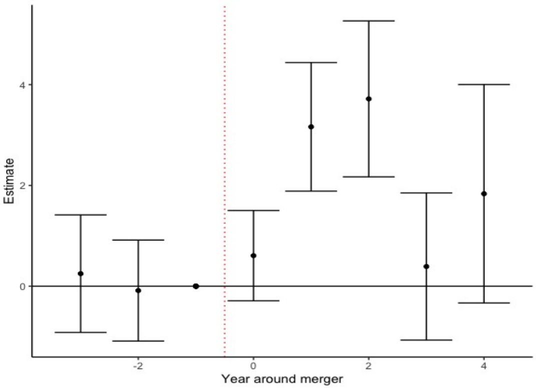
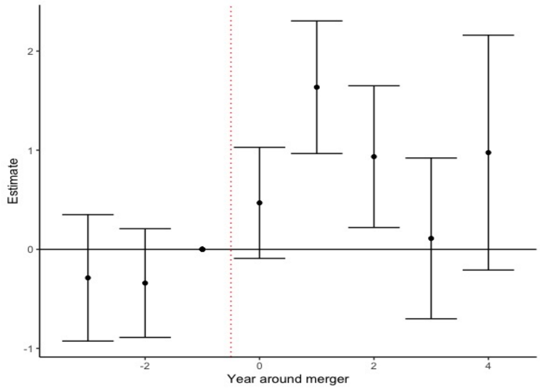


Figure 4: Difference in house prices between overlapped and non-overlapped properties around mergers

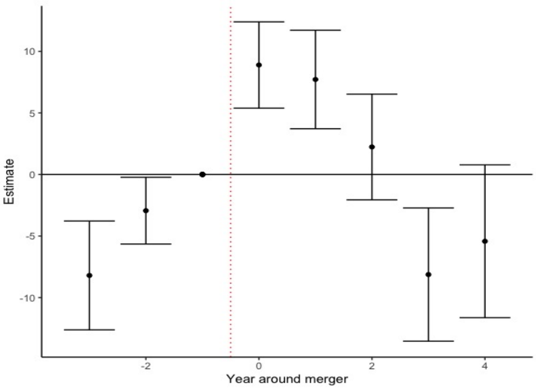
This figure presents the coefficients from a staggered difference-in-differences regression of the Zillow Rent Index in relation to the mergers. A zip is treated if the acquirer increases its concentration of ownership as a result of the merger. Control zips include all zips in which the acquirer owned at least one property prior to the merger. I include county x year and zip fixed effects in the regression, and cluster standard errors at the zip level. The horizontal axis shows three years prior to the merger until four years after the merger. The vertical access represents the difference between treated and control zips in terms of the natural logarithm of the Zillow House Price Index. Each estimate is presented with 95% error bands.



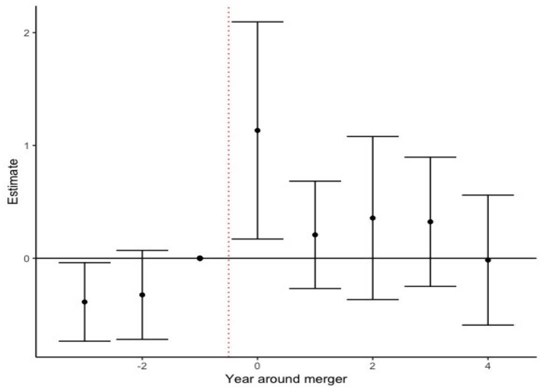
(a) Permits Issued to Owner Occupiers



(b) Permits Issued to Small Investors



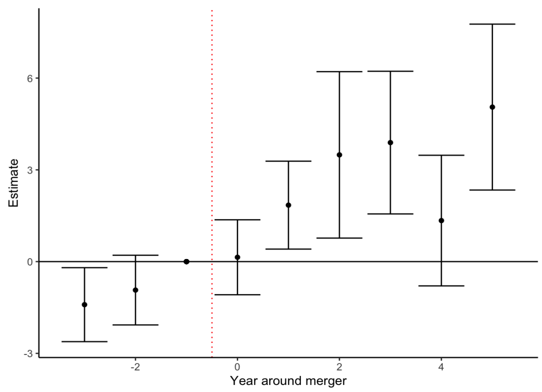
(c) Permits Issued to Large Investors



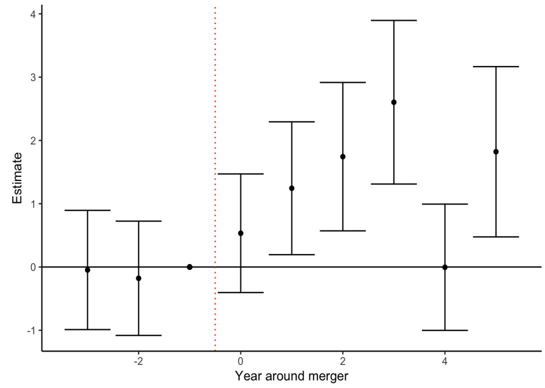
(d) Permits Issued to SFR Investors

Figure 5: Difference in permits by investor type between overlapped and non-overlapped properties around mergers

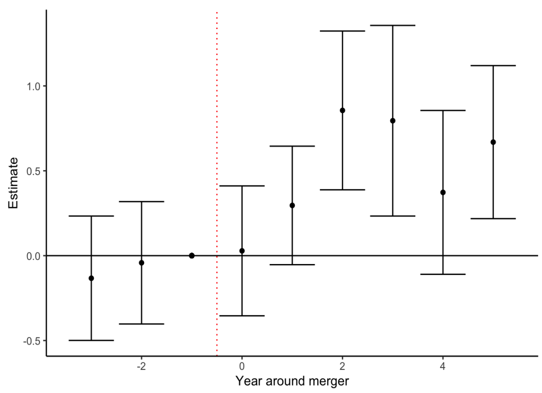
This figure presents the coefficients from a regression of permit issuances by investor type on the interaction between treatment and the year in relation to the merger. A census tract is treated if the acquirer gained at least one property in tract t as a result of the merger. Control tracts include all tracts in which the acquirer owned at least one property prior to the merger. I include county x year and tract fixed effects in the regression, and cluster standard errors at the tract level. I include controls as specified in equation **??**. The horizontal axis shows three years prior to the merger until four years after the merger. The vertical access represents the difference between treated and control tracts in terms of the number of permits issued. Each estimate is presented with 95% error bands.



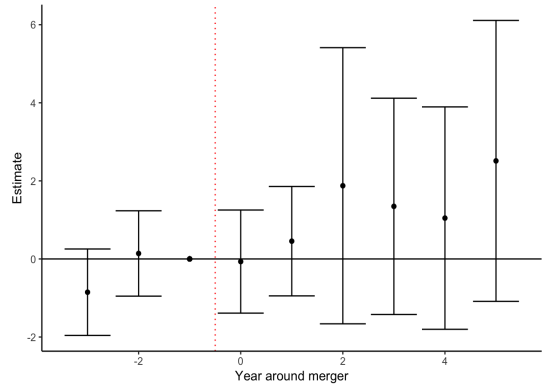
(a) All Improvement Applications



(b) Black Improvements Applications

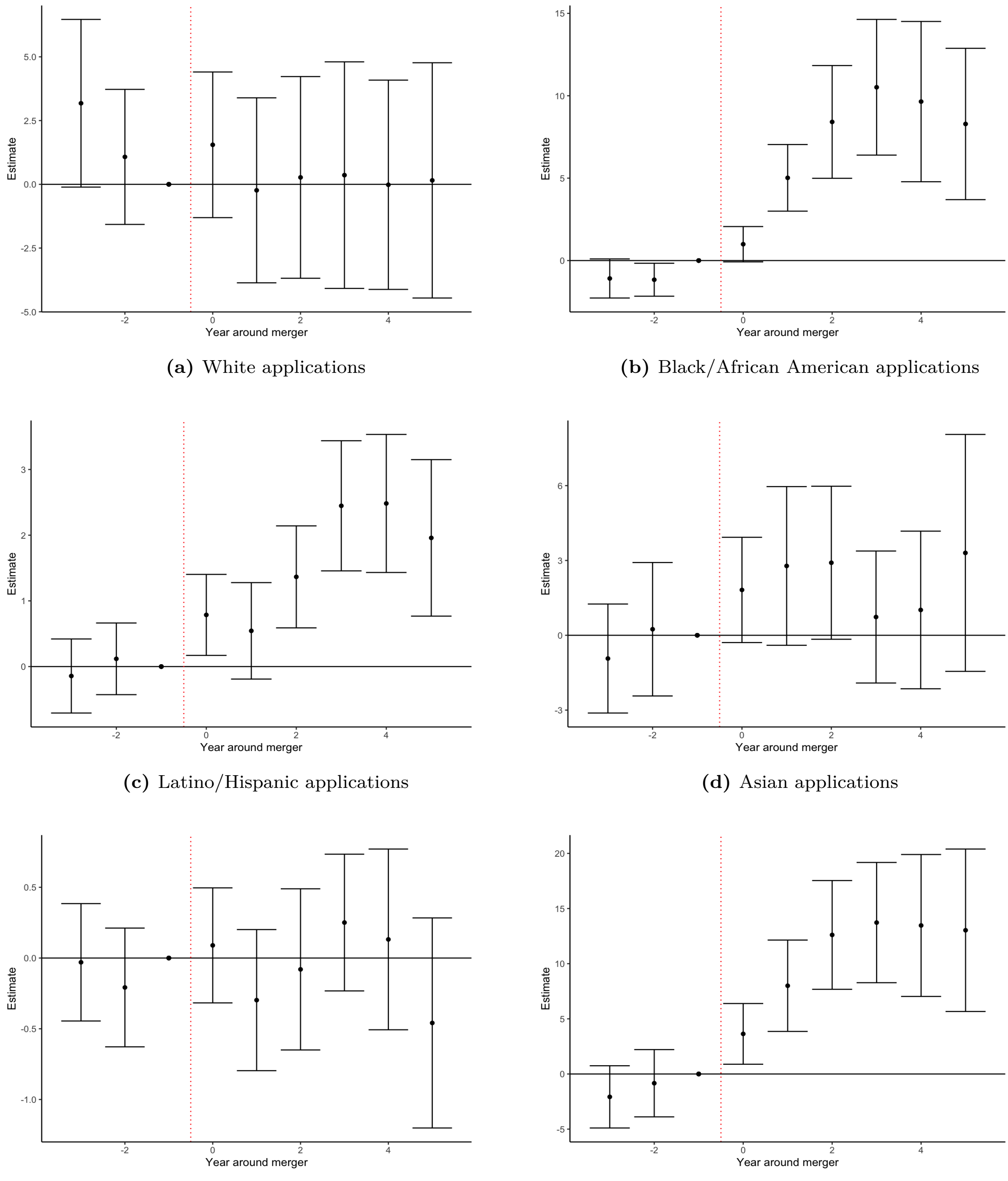


(c) Latino Improvements Applications



(d) White Improvements Loans

Figure 6: Difference in applications for home improvements loans by investor groups between overlapped and non-overlapped properties around mergers
This figure presents the coefficients from a regression of the count of home improvements loan applications by investor group around mergers. A census tract is treated if the acquirer increased its concentration of ownership as a result of a merger. Control tracts include all tracts in which the acquirer owned at least one property prior to the merger. I include county x year and tract fixed effects in the regression, and cluster standard errors at the tract level. I include controls as specified in equation X. The horizontal axis shows three years prior to the merger until five years after the merger. The vertical access represents the difference between treated and control tracts in terms of the natural logarithm of mortgage applications. Each estimate is presented with 95% error bands.



(a) White applications

(b) Black/African American applications

(c) Latino/Hispanic applications

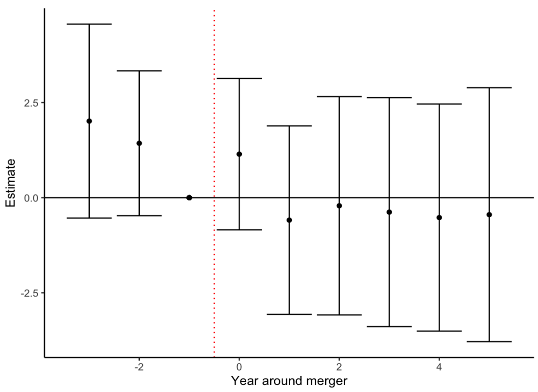
(d) Asian applications

(e) Mixed-race/ethnicity applications

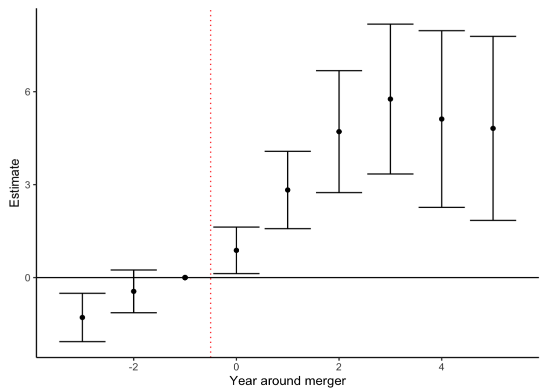
(f) Non-white applications

Figure 7: Difference in mortgage applications by race/ethnicity between overlapped and non-overlapped properties around mergers

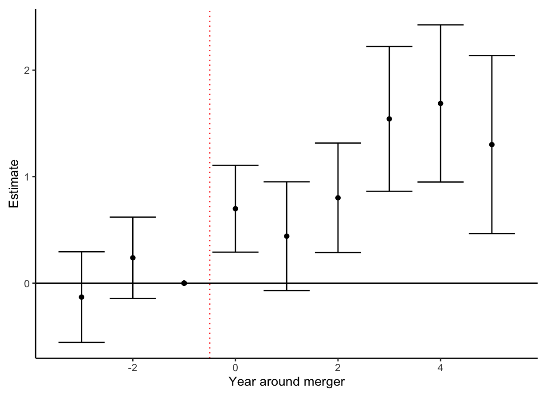
This figure presents the coefficients from the Sun Abraham estimation mortgage applications by race in treated versus control census tracts. A census tract is treated if the acquirer increased its concentration of ownership in a neighborhood as a result of a merger. Control tracts include all tracts in which the acquirer owned at least one property prior to the merger. I include county x year and tract fixed effects as well as controls in the regression, and cluster standard errors at the tract level. The horizontal axis shows three years prior to the merger until five years after the merger. The vertical access represents the difference between treated and control tracts in terms of the natural logarithm of mortgage applications. Each estimate is presented with 95% error bands.



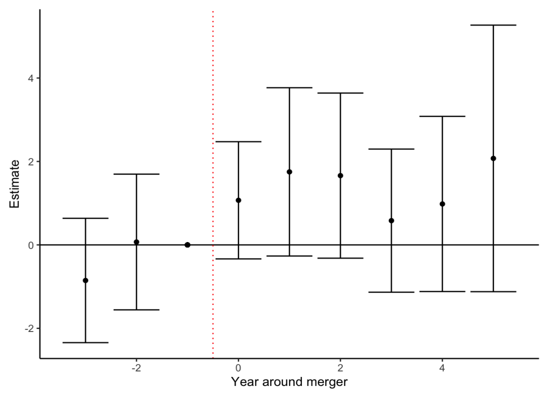
(a) White mortgage originations



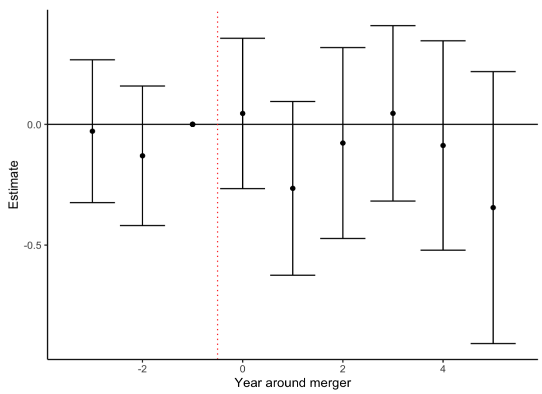
(b) Black/African American mortgage originations



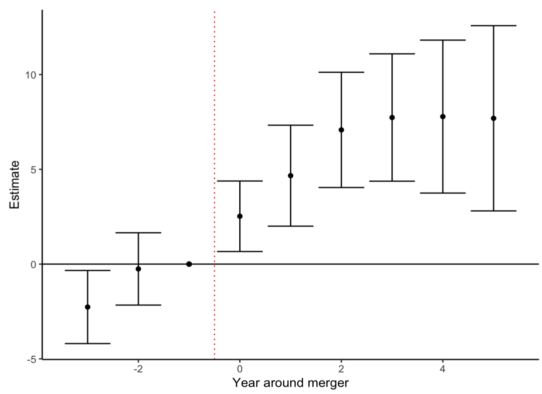
(c) Latino/Hispanic mortgage originations



(d) Asian mortgage originations



(e) Mixed-race/ethnicity mortgage originations



(f) Non-white mortgage originations

Figure 8: Difference in mortgage originations by race/ethnicity between overlapped and non-overlapped properties around mergers

This figure presents the coefficients from the Sun Abraham estimation mortgage applications by race in treated versus control census tracts. A census tract is treated if the acquirer increased its concentration of ownership in a neighborhood as a result of a merger. Control tracts include all tracts in which the acquirer owned at least one property prior to the merger. I include county x year and tract fixed effects in the regression, and cluster standard errors at the tract level. The horizontal axis shows three years prior to the merger until five years after the merger. The vertical access represents the difference between treated and control tracts in terms of the natural logarithm of mortgage applications. Each estimate is presented with 95% error bands.

Table 1: Summary of mergers in analysis

Acquirer				Target				Transaction Details		
Name	Status	Properties in ATL	% Portfolio in ATL	Name	Status	Properties in ATL	% Portfolio in ATL	Announced Date	Completion Date	Transaction Value (US$m)
Invitation Homes	Public	7,517	20.6%	Colony Starwood Homes	Public	5,540	17.8%	10 Aug 2017	16 Nov 2017	8,604
Starwood Waypoint	Public	2,475	19.2%	Colony American	Private	3,206	18.0%	21 Sep 2015	5 Jan 2016	7,700
Tricon American Homes	Public	1,062	13.7%	Silver Bay Realty Trust	Public	2,949	32.6%	27 Feb 2017	9 May 2017	1,503
American Homes 4 Rent	Public	2,802	7.2%	American Residential Properties	Public	1,062	11.9%	3 Dec 2015	29 Feb 2016	1,429

This table presents details of the horizontal mergers of institutional SFR investors used in the analysis in the paper. The number (percentage) of properties in Atlanta are those reported in each company's annual report in the year prior to the merger. Note that Colony American was private before its acquisition by Starwood Waypoint so its financial statements are not public. However, the December 2015 10-K for Starwood Waypoint provides pre- and post-merger portfolio composition from which it is straightforward to calculate Colony American's exposure to Atlanta. Transaction size and transaction annoucement/closed dates come from CapitalIQ. Where this information is missing from CapitalIQ (e.g. in the merger of Colony American and Starwood Waypoint) this information is found in press releases contained in SEC filings relating to the merger.

Table 2: Summary statistics

(a) Zip level statistics

Statistic:	N	Mean	P1	Median	P99	SD
Properties (per merger):	169	56.630	0.000	2.000	700.08	143.927
Δ Properties (per merger):	169	28.26	0.000	0.000	360.760	77. 977

(b) Census tract level statistics

Statistic:	N	Mean	P1	Median	P99	SD
Properties (per merger):	981	9.294	0.000	1.667	70.600	17. 521
Δ Properties (per merger):	981	4.650	0.000	0.667	37.400	10.622

(c) Market Share

Statistic:	N	Mean	P1	Median	P99	SD
Zip level:						
Large treatment (pre-merger):	50	0.034	0.005	0.022	0.139	0.034
Large Treatment (post-merger):	50	0.071	0.009	0.050	0.272	0.064
Small treatment (pre-merger):	67	0.013	0.000	0.006	0.089	0.029
Small treatment (post-merger):	67	0.020	0.001	0.011	0.152	0.035
No treatment:	35	0.007	0.001	0.005	0.027	0.007
Census tract level:						
Large treatment (pre-merger):	200	0.066	0.010	0.050	0.210	0.048
Large Treatment (post-merger):	200	0.136	0.030	0.109	0.445	0.089
Small treatment (pre-merger):	448	0.023	0.001	0.016	0.149	0.027
Small treatment (post-merger):	448	0.047	0.005	0.035	0.247	0.047
No treatment:	298	0.026	0.001	0.012	0.312	0.066

This table presents summary statistics for the data used in this paper. Panel A and B present details on the number of properties and change in properties as a result of mergers in zip and census tracts. $Properties(permerger)$ is the average number of properties owned by the merged firms in each zip or census tract. $\Delta Properties(permerger)$ is the number of properties gained by the acquiring firm after each merger in the zip or census tract. Panel C presents the acquirers' market share in overlapped zips and census tracts before and after the merger. Market share is measured by the ratio of the number of properties owned by the merged firm to the number of investor owned properties in a zip or census tract. A neighbourhood is defined as having a"large treatment" if the acquirer gains 20 (10) or more properties in the zip (census tract) as a result of the merger. A neighbourhood is defined as "small treatment" if the acquirer gained at least one but less than 20 (10) properties in that zip (census tract) as a result of the merger.

Table 3: Summary Statistics: Prices and Improvements

(a) Rent Prices

Period:	Pre merger			Post merger		
Statistic:	N	Mean	SD	N	Mean	SD
American Homes 4 Rent	1307	1203	112	2092	1381	137
American Residential Properties	736	1214	123	1771	1350	154
Colony American	1797	1153	124	3742	1272	174
Invitation Homes	4944	1233	131	7438	1440	156
Starwood Waypoint	1393	1156	111	3285	1299	169
All	10177	1203	129	18328	1365	175
$I(\Delta Properties) \geq 1$	9914	1205	128	17896	1367	175
$I(\Delta Properties) \geq 20$	8838	1209	124	16473	1368	176
$I(\Delta Properties) = 0$	223	1137	127	290	1332	127

(b) House Prices

Period:	Pre merger			Post merger		
Statistic:	N	Mean	SD	N	Mean	SD
American Homes 4 Rent	63	183223	47086	63	222304	52073
American Residential Properties	565	184612	49286	2002	208513	60067
Colony American	1901	167173	56258	4256	190424	61156
Invitation Homes	5253	185358	56273	8460	232618	57951
Starwood Waypoint	1208	169640	58380	3562	199215	57365
All	10224	179807	54479	20831	214706	60598
$I(\Delta Properties) \geq 1$	86	179719	52425	86	214223	58328
$I(\Delta Properties) \geq 20$	52	176133	42885	52	210251	50966
$I(\Delta Properties) = 0$	30	177974	82342	30	226354	87622

This table presents estimates of difference-in-difference regressions of local rent and house prices around the three mergers of institutional investors. The sample includes the property valuations of properties in merged neighbourhoods, as well as properties in neighbourhoods where at least one acquiring firm owned a property prior to the acquisition. The dependent variable in (a) is the natural logarithm of the Zillow Zip Rental Index of each zip and in (b) is the natural logarithm of the Zillow House Price Index in each zip. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and zip fixed effects in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 4: Change in neighbourhood prices around mergers

(a) Rent Prices

Dependent variable:	ln(Rent)	
Treatment Variable:	TWFE	Sun & Abraham 2021
PostxTreat	0.0493**	0.0503***
	(2.489)	(2.844)
CountyxYear FE	Yes	Yes
Zip FE	Yes	Yes
Adjusted R^2	0.973	0.977
Observations	599	599

(b) House Prices

Dependent variable:	ln(HousePrice)	
Treatment Variable:	TWFE	Sun & Abraham 2021
PostxTreat	0.0309*	0.0301**
	(1.918)	(1.982)
CountyxYear FE	Yes	Yes
Zip FE	Yes	Yes
Adjusted R^2	0.983	0.983
Observations	1,324	1,324

This table presents estimates of staggered difference-in-difference regressions of local rent and house prices around the four mergers of institutional investors. The sample includes the property valuations of properties in merged neighbourhoods, as well as properties in neighbourhoods where at least one acquiring firm owned a property prior to the acquisition. The dependent variable in (a) is the natural logarithm of the Zillow Zip Rental Index of each zip and in (b) is the natural logarithm of the Zillow House Price Index in each zip. In column 1 is the TWFE regression where the acquirer gained at least one additional property in a neighbourhood as a result of the merger. Estimates using Sun Abraham (2021)'s approach are in column 2. I include county x year and zip fixed effects in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 5: Home Improvements Loans by Owner Type

(a) Mean Value of Applications for Home Improvements Loans

Dependent Variable	Treatment Variable:	Applications	Originations
Improvements Loans	Post x Treat	4.097***	1.090
		(1.457)	(0.874)
	Adjusted R^2	0.801	0.767
Black Improvements Loans	Post x Treat	1.326***	0.307*
		(0.459)	(0.172)
	Adjusted R^2	0.780	0.503
Latino Improvements Loans	Post x Treat	0.501***	0.121
		(.173)	(0.086)
	Adjusted R^2	0.458	0.245
White Improvements Loans	Post x Treat	1.181	0.436
		(1.147)	(0.702)
	Adjusted R^2	0.813	0.762
All regressions	CountyxYear FE	Yes	Yes
	Tract FE	Yes	Yes
	Controls	Yes	Yes
	Observations	3,794	3,794

This table presents estimates from staggered difference-in-difference regressions following the Sun and Abraham approach of home improvement loans by owner type around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The time period includes from three years before the merger until four years after. The dependent variable for each regression is (a) the count of home improvement applications in each tract or (b) the count of loan originations for home improvements in each tract. I include county x year and tract fixed effects in each regression as well as control variables per equation X. I report standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 6: Permitting Activity by Owner Type

Dependent Variable		
	Treatment Variable:	Sun & Abraham
Owner Occupier	Post x Treat	5.075***
		(0.619)
	Adjusted R^2	0.528
Small Investor	Post x Treat	-2.344***
		(0.687)
	Adjusted R^2	0.411
Large Investor	Post x Treat	9.761
		(5.896)
	Adjusted R^2	0.450
Institutional Investor	Post x Treat	-0.326
		(0.277)
	Adjusted R^2	0.019
All regressions	CountyxYear FE	Yes
	Tract FE	Yes
	Controls	Yes
	Observations	965

This table presents estimates of difference-in-difference regressions of permit activity by owner type around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The time period includes from three years before the merger until four years after. The dependent variable for each regression is the natural logarithm of 1 + the permits issued to each type of investor in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression as well as control variables per equation X. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 7: Mortgage applications by race/ethnicity around mergers

Dependent Variable			
	Estimation Method:	TWFE	Sun Abraham (2021)
(1) Black/African American	Post x Treat	7.574***	7.113**
		(4.862)	(4.718)
	Adjusted R^2	0.766	0.768
(2) White	Post x Treat	-1.027	0.352
		(-0.663)	(0.201)
	Adjusted R^2	0.930	0.930
(3)Latino/Hispanic	Post x Treat	1.528***	1.587***
		(4.609)	(4.651)
	Adjusted R^2	0.738	0.739
(4) Asian	Post x Treat	2.263**	2.080
		(2.382)	(1.436)
	Adjusted R^2	0.777	0.776
(5) Native American	Post x Treat	0.066**	-0.0124
		(2.116)	(-0.331)
	Adjusted R^2	0.0715	0.700
(6) Mixed Race/Ethnicity	Post x Treat	0.0237	-0.0558
		(0.144)	(-0.262)
	Adjusted R^2	0.539	0.539
(7) Non-White	Post x Treat	11.267***	10.695***
		(5.676)	(4.640)
	Adjusted R^2	0.774	0.775
All regressions	CountyxYear FE	Yes	Yes
All regressions	Tract FE	Yes	Yes
All regressions	Observations	6,486	6,486

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The time period includes three years before each merger until four years after. The dependent variable for each regression is the application count in each tract. Column 1 includes the estimate from a TWFE regression. Column 2 presents the estimates from the Sun and Abraham (2021) approach. I include county x year, tract fixed effects and a series of controls detailed in equation **??** in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 8: Mortgage originations by race/ethnicity around mergers

Dependent Variable	Estimation Method:	TWFE	Sun Abraham (2021)
(1) Black/African American	Post x Treat	4.418***	4.000**
		(4.706)	(4.440)
	Adjusted R^2	0.739	0.741
(2) White	Post x Treat	-1.260	-0.161
		(-1.167)	(-0.130)
	Adjusted R^2	0.928	0.927
(3)Latino/Hispanic	Post x Treat	0.983***	1.072***
		(4.367)	(4.569)
	Adjusted R^2	0.725	0.726
(4) Asian	Post x Treat	1.567**	1.344
		(2.473)	(1.433)
	Adjusted R^2	0.784	0.784
(5) Native American	Post x Treat	0.00938	-0.0189
		(0.428)	(-0.725)
	Adjusted R^2	0.0410	0.0394
(6) Mixed Race/Ethnicity	Post x Treat	-0.0610	-0.111
		(-0.529)	(-0.726)
	Adjusted R^2	0.519	0.519
(7) Non-White	Post x Treat	6.809***	6.215***
		(5.395)	(4.250)
	Adjusted R^2	0.775	0.775
All regressions	CountyxYear FE	Yes	Yes
All regressions	Tract FE	Yes	Yes
All regressions	Observations	6,486	6,486

This table presents estimates of difference-in-difference regressions of mortgage originations by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The time period includes three years before each merger until four years after. The dependent variable for each regression is the application count in each tract. Column 1 includes the estimate from a TWFE regression. Column 2 presents the estimates from the Sun and Abraham (2021) approach. I include county x year, tract fixed effects and a series of controls detailed in equation **??** in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 9: Tax Assessor Appeals by Investor Type

Dependent variable:	$Appeals_{i,t}$		
	(1)	(2)	(3)
Intercept	-4.671***	-3.215***	-10.322***
	(0.013)	(0.731)	(0.772)
SFR	3.070***	3.335***	3.388***
	(0.020)	(0.022)	(0.023)
Tiny Investor	0.572***	0.515***	0.573***
	(0.025)	(0.026)	(0.029)
Small Investor	1.098***	1.017***	1.159***
	(0.025)	(0.027)	(0.031)
Medium Investor	2.115***	2.006***	2.417***
	(0.025)	(0.027)	(0.032)
Large Investor	2.427***	2.343***	2.862***
	(0.018)	(0.020)	(0.25)
log(Tax Assessor Valuation$_{i,t}$)			0.282***
			(0.008)
Tract-Year FE:	N	Y	Y
Observations	971,282	913,720	865,075

This table presents estimates of a logistic regression of appeals by investor type. The sample includes all property appeals in two counties (Paulding and Douglas) between 2012-2021. The dependent variable is the incidence of an appeal in property i during year t. SFR indicates the owner of property i is an SFR company. Other investor types include: tiny investor (owns 1 investment property); small investor (owns between 2-10 investment properties); medium investor (owns between 10-50 investment properties); large investor (owns over 50 investment properties). The reference level is an owner-occupier. In (3) I include the logarithm of the tax assessor valuation for property i in year t. I include tract x year fixed effects in some specifications. I report standard errors clustered by property in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 10: Probability of Appeals by Investor Type

Investor Type:	Owner Occupier	Tiny Investor	Small Investor	Medium Investor	Large Investor	SFR Investor
	0.009	0.016	0.027	0.072	0.096	0.168

This table presents estimates of probability of appeals by investor type from the regression in Table 9 column (1).

Table 11: Success of Appeals by Investor Type

Dependent variable:	Successful Appeal$_{i,t}$			
	(1)	(2)	(3)	(4)
Intercept	0.121***	0.170***	0.167***	1.244***
	(0.025)	(0.039)	(0.039)	(0.174)
SFR	-0.242***	0.106**	0.237***	0.220***
	(0.046)	(0.050)	(0.052)	(0.052)
Tiny Investor	0.113***	0.050	0.068	0.065
	(0.044)	(0.046)	(0.046)	(0.046)
Small Investor	0.309***	0.252***	0.252***	0.200***
	(0.043)	(0.045)	(0.045)	(0.046)
Medium Investor	0.714***	0.649***	0.621***	0.490***
	(0.048)	(0.049)	(0.051)	(0.55)
Large Investor	1.149***	0.985***	0.990***	0.804***
	(0.036)	(0.038)	(0.038)	(0.049)
Evidence$_{i,t}$			1.658***	1.626***
			(0.067)	(0.062)
log(Tax Assessor Valuation$_{i,t}$)				-0.088***
				(0.014)
County FE:	N	Y	Y	Y
Year FE:	N	Y	Y	Y
Observations	971,282	913,720	865,075	

This table presents estimates of a logistic regression of appeals by investor type. The sample includes all property appeals in two counties (Paulding and Douglas) between 2012-2021. The dependent variable is the incidence of an appeal in property i during year t. SFR indicates the owner of property i is an SFR company. Other investor types include: tiny investor (owns 1 investment property); small investor (owns between 2-10 investment properties); medium investor (owns between 10-50 investment properties); large investor (owns over 50 investment properties). The reference level is an owner-occupier. In (3) I include the logarithm of the tax assessor valuation for property i in year t. I include tract x year fixed effects in some specifications. I report standard errors clustered by property in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 12: Reduction in Assessed Value of Successful Appeals by Investor Type

Dependent variable:	Reduction in Value due to Appeal$_{i,t}$	
	(Unscaled)	(Scaled)
SFR	-0.585***	-0.281
	(-12.763)	(-0.387)
Tiny Investor	0.618***	-0.516
	(4.026)	(-0.279)
Small Investor	0.300***	-0.217
	(3.713)	(-0.172)
Medium Investor	-0.237***	-0.059
	(-4.002)	(-0.125)
Large Investor	-0.473***	-0.113
	(-12.320)	(-0.140)
Evidence$_{i,t}$	0.153	-0.509
	(4.431)	(-0.466)
Tract FE:	Y	Y
Year FE:	Y	Y
Observations	17,024	2,189
R^2	11.32%	5.59%

This table presents estimates of the reduction in taxable home value as a result of a successful appeal by investor type. The sample includes all successful property appeals in two counties (Paulding and Douglas) between 2010-2021. The unscaled dependent variable is the logarithm of the difference between the tax assessors' property valuation and the final valuation resolved upon during the appeal. The scaled dependent variable is the difference between the tax assessors' property valuation and the final valuation divided by the difference between the tax assessors' valuation and the valuation asserted by the taxpayer. In other words, the scaled dependent variable measures the degree of success of the appeal (i.e. the reduction in the final value scaled by the distance between the tax assessor's and the taxpayer's initial valuations). SFR indicates the owner of property i is an SFR company. Other investor types include: tiny investor (owns 1 investment property); small investor (owns between 2-10 investment properties); medium investor (owns between 10-50 investment properties); large investor (owns over 50 investment properties). The reference level is an owner-occupier. I also include a dummy variable, Evidence$_{i,t}$, that equals 1 if the taxpayer presented evidence with their appeal. I include tract x year fixed effects in all specifications. I cluster standard errors by property and report t-statistics in parenthesis.. *p<0.1; **p<0.05; ***p<0.01

Table 13: Difference between Assessed Value and Sale Price by Investor Type

Dependent variable:	log(Δ Assessed Value and Sale Price$_{i,t}$)		
	(1)	(2)	(3)
SFR	4.487***	4.413***	4.121***
	(5.886)	(5.621)	(4.782)
Tiny Investor	0.149	0.125	-0.085
	(0.119)	(0.102)	(-0.065)
Small Investor	0.878	0.841	0.357
	(0.787)	(0.745)	(0.303)
Medium Investor	3.074***	3.051***	2.493**
	(3.177)	(3.105)	(2.439)
Large Investor	4.430***	4.406***	3.602***
	(3.839)	(3.747)	(2.929)
I(Previous Appeal > 0)		8.395***	
		(13.330)	
# Previous Appeals			0.915***
			(4.881)
Tract FE:	Y	Y	Y
Year FE:	Y	Y	Y
Observations:	3,753	3,753	3,753
R^2	63.78%	63.82%	65.52%

This table presents estimates of the difference between assessed value and sale price by investor type. The sample includes all sales in two counties (Paulding and Douglas) between 2010-2021. The dependent variable is the logarithm of the difference between the property valuation and sale price. SFR indicates the owner of property i is an SFR company. Other investor types include: tiny investor (owns 1 investment property); small investor (owns between 2-10 investment properties); medium investor (owns between 10-50 investment properties); large investor (owns over 50 investment properties). The reference level is an owner-occupier. In (2) I include a dummy variable, I(Previous Appeal > 0), that is equal to 1 if the property has had one or more appeals against its valuation. In (3) I include the number of appeals the property has had against its valuation in the sample period. I include tract x year fixed effects in all specifications. I cluster standard errors by property and report t-statistics in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Appendices

Appendix A. Proofs and Derivations

Appendix A.1. Demand Functions with Differentiated/Undifferentiated Houses

Consider the demand if the low-quality property is not dominated.[40] Renters with a taste parameter exceeding $(r_2 - r_1)/(s_2 - s_1)$ rent the high quality property, those with a taste parameter between $r_1/(s_2 + \alpha(s_1 + s_2))$ and $(r_2 - r_1)/(s_2 - s_1)$ rent the low quality property, and the others do not rent at all. Hence, the demand for the high quality property is:

$$D_1(r_1, r_2) = \begin{cases} \bar{\theta} - \frac{r_1}{s_1+\alpha(s_1+s_2)} & \text{if } r_1 < \frac{s_1+\alpha(s_1+s_2)}{s_2+\alpha(s_1+s_2)} r_2 \\ \bar{\theta} - \frac{r_1 - r_2}{s_1 - s_2} & \text{if } \frac{s_1+\alpha(s_1+s_2)}{s_2+\alpha(s_1+s_2)} r_2 \leq r_1 \leq r_2 + \bar{\theta}(s_1 - s_2) \\ 0 & \text{if } r_1 > r_2 + \bar{\theta}(s_1 - s_2) \end{cases} \quad \text{(Appendix 1)}$$

and demand for the low quality house is given by

$$D_2(r_1, r_2) = \begin{cases} \bar{\theta} - \frac{r_2}{s_2+\alpha(s_1+s_2)} & \text{if } r_2 < r_1 - \bar{\theta}(s_1 - s_2) \\ \frac{r_1 - r_2}{s_1 - s_2} - \frac{r_2}{s_2+\alpha(s_1+s_2)} & \text{if } r_1 - \bar{\theta}(s_1 - s_2) \leq r_2 \leq r_1 \frac{s_2+\alpha(s_1+s_2)}{s_1+\alpha(s_1+s_2)} \\ 0 & \text{if } r_2 > r_1 \frac{s_2+\alpha(s_1+s_2)}{s_1+\alpha(s_1+s_2)} \end{cases} \quad \text{(Appendix 2)}$$

Appendix A.2. Optimal Price and Quality with Competition

I first derive the equilibrium in the price setting game, taking the quality of each house as fixed. Each renter's quality preference is private information but the distribution of these quality preferences is known prior to the landlord's pricing decision. Without excess demand (or capacity-constraint) the Bertrand paradox for undifferentiated goods applies: rent will be set at a level equal to the cost of providing the unit. Hence, both investors are better off if one investor makes improvements to their house, so they compete in a differentiated houses game. Profits are given as $\Pi_1(r_1, r_2) = r_1 D_1(r_1, r_2)$ and $\Pi_2(r_1, r_2) = r_2 D_2(r_1, r_2)$. Hence, the best response function for the high quality landlord is:

$$\psi_1(r_2) = \begin{cases} \frac{\bar{\theta}(s_1 - s_2) + r_2}{2} & \text{if } r_2 \leq \frac{\bar{\theta} s_2 (s_1 - s_2)}{2s_1 - s_2} \\ r_2 \frac{s_1+\alpha(s_1+s_2)}{s_2+\alpha(s_1+s_2)} & \text{if } \frac{\bar{\theta} s_2 (s_1 - s_2)}{2s_1 - s_2} < r_2 \leq \frac{\bar{\theta}(s_2+\alpha(s_1+s_2))}{2} \\ \frac{\bar{\theta}(s_1+\alpha(s_1+s_2))}{2} & \text{if } r_2 > \frac{\bar{\theta}(s_2+\alpha(s_1+s_2))}{2} \end{cases} \quad \text{(Appendix 3)}$$

And the best response function for the low quality landlord is given by:

[40] The low quality house will be dominated if the quality per dollar for the high quality property is higher such that $(s_2 + \alpha(s_1 + s_2))/r_2 \geq (s_1 + \alpha(s_1 + s_2))/r_1$. In that case all renters prefer the high quality property to the low quality property (if they rent at all), so demand for the high quality property is given as $D(r_2) = N[1 - F(r_2/(s_2 + \alpha(s_1 + s_2)))]$ and demand for the low quality property is zero.

$$\psi_2(r_1) = \begin{cases} \frac{r_1(s_2+\alpha(s_1+s_2))}{2(s_1+\alpha(s_1+s_2))} & \text{if } r_1 \leq \frac{2\bar{\theta}(s_1+\alpha(s_1+s_2))(s_1-s_2)}{2s_1-s_2+\alpha(s_1+s_2)} \\ r_1 - \theta(s_1 - s_2) & \text{if } \frac{2\bar{\theta}(s_1+\alpha(s_1+s_2))(s_1-s_2)}{2s_1-s_2+\alpha(s_1+s_2)} < r_1 \leq \bar{\theta}[s_1 - \frac{s_2+\alpha(s_1+s_2)}{2}] \\ \frac{\bar{\theta}(s_2+\alpha(s_1+s_2))}{2} & \text{if } r_1 > \bar{\theta}[s_1 - \frac{s_2+\alpha(s_1+s_2)}{2}] \end{cases} \quad \text{(Appendix 4)}$$

These best response functions intersect where the high quality landlord charges rent of $r_1^* = \frac{2(s_1+\alpha(s_1+s_2))\bar{\theta}(s_1-s_2)}{4s_1-s_2+3\alpha(s_1+s_2)}$ and the low quality landlord charges rent of $r_2^* = \frac{(s_2+\alpha(s_1+s_2))\bar{\theta}(s_1-s_2)}{4s_1-s_2+3\alpha(s_1+s_2)}$. This is the unique pure strategy price equilibrium. Note that these rents are strictly higher than what each landlord would charge where there is no utility spillover from the other property. [41]

Given these prices, the quantity demanded of the high quality property is $D_1^* = \frac{\bar{\theta}(2s_1+3\alpha(s_1+s_2))}{4s_1-s_2+3\alpha(s_1+s_2)}$ and the equilibrium payoff to the high quality landlord is $\Pi_1^*(s_1, s_2) = \frac{\bar{\theta}^2(s_1-s_2)(4s_1+6\alpha(s_1+s_2))(s_1+\alpha(s_1+s_2))}{(4s_1-s_2+3\alpha(s_1+s_2))^2}$. Similarly, the quantity demanded of the low quality property is $D_2^* = \frac{\bar{\theta}(s_1+\alpha(s_1+s_2))}{4s_1-s_2+3\alpha(s_1+s_2)}$, and the equilibrium payoff to the low quality landlord is $\Pi_2^*(s_1, s_2) = \frac{\bar{\theta}^2(s_1-s_2)(s_1s_2+\alpha(1+\alpha)(s_1+s_2)^2)}{(4s_1-s_2+3\alpha(s_1+s_2))^2}$. [42]

In the first stage, each landlord decides whether to make improvements to their house given these profit functions. If demand is met by the existing rental stock, the high quality firm chooses quality to maximise its profits less the cost of improvement, $\pi_1 = \Pi_1(s_1, s_2) - c_1$. The first order condition of this problem is:

$$\frac{\partial \pi_i}{\partial s_i} = \frac{2\bar{\theta}^2(2s_1(4s_i^2 - 3s_is_j + 2s_j^2) + 9\alpha^3(s_1+s_2)^3 + 3\alpha^2(9s_1^3 + 12s_1^2s_2 + 7s_1s_2^2 + 4s_2^3))}{(4s_1 - s_j + 3\alpha(s_1+s_2))^3} + \frac{2\bar{\theta}^2\alpha(26s_1^3 + 3s_1^2s_2 + 8s_1s_2^2 + 5s_2^3)}{(4s_1 - s_j + 3\alpha(s_1+s_2))^3} - s_1 = 0 \quad \text{(Appendix 5)}$$

Equally, the low quality firm will maximise its profits less the cost of improvement, $\pi_2 = \Pi_2(s_1, s_2) - c_2$. The first order condition of this problem is:

$$\frac{\partial \pi_j}{\partial s_j} = \frac{\bar{\theta}^2(s_i^2(4s_i - 7s_j) + 3\alpha^3(s_1+s_2)^3 + \alpha^2(16s_1^2s_2 - 3s_1^3 + 21s_1s_2^2 + 2s_2)}{(4s_i - s_j + 3\alpha(s_1+s_2))^3} + \frac{\bar{\theta}^2\alpha(9s_1^3 - 16s_1^2s_2 - 12s_1s_2^2 + s_2^3)}{(4s_i - s_j + 3\alpha(s_1+s_2))^3} - s_j = 0 \quad \text{(Appendix 6)}$$

[41] Compare this to the differentiated goods equilibrium where there is no spillover from shared improvements. In that case $r_1^* = \frac{2s_1\bar{\theta}(s_1-s_2)}{4s_1-s_2}$ and the low quality landlord charges rent of $r_2^* = \frac{s_2\bar{\theta}(s_1-s_2)}{4s_1-s_2}$. These rents are both strictly less than is obtained if renters obtain utility from a higher quality neighborhood (i.e. if there are positive externalities to neighborhood improvement).

[42] Compare with the payoff if there are no spillovers from quality. In that case, $D_1^* = \frac{2\bar{\theta}s_1}{4s_1-s_2}$ and the equilibrium payoff to the high quality landlord is $\Pi_1^*(s_1s_2) = \frac{4\bar{\theta}^2s_1^2(s_1-s_2}{(4s_1-s_2)^2}$. Similarly, the quantity demanded of the low quality property is $D_2^* = \frac{\bar{\theta}s_1}{4s_1-s_2}$, and the equilibrium payoff to the low quality landlord is $\Pi_2^*(s_1, s_2) = \frac{\bar{\theta}s_1s_2(s_1-s_2}{(4s_1-s_2)^2}$.

Appendix A.3. Merged Landlords

If the merged landlord offers houses of the same quality, she faces demand equal to:

$$D(r_i, s_i) = \bar{\theta} - \frac{r_i}{(1+2\alpha)s}$$

Profits are $r_i D(r_i, s_i)$ so the profit-maximising price is equal to $r_i = \bar{\theta}s(1+2\alpha)/2$ and the optimal choice of quality is $s_i = \theta^2(1+2\alpha)/4$.

Consider the optimal price and quality if the landlord decides to split the market by offering two qualities of houses. The merged landlord faces a profit function equal to:

$$\Pi(r_1, r_2, s_1, s_2) = \Big[\bar{\theta} - \frac{r_1 - r_2}{s_1 - s_2}\Big]\Big(r_1 - \frac{s_1^2}{2}\Big) + \Big[\frac{r_1 - r_2}{s_1 - s_2} - \frac{r_2}{s_2 + \alpha(s_1 + s_2)}\Big]\Big(r_2 - \frac{s_2^2}{2}\Big)$$

Hence, the optimal choice of rental price for the high quality house is $r_1^* = \bar{\theta}(s_1 - s_2)/(2(1-z))$ and the optimal rental price for the low quality house is $r_2^* = \bar{\theta}z(s_1 - s_2)/(2(1-z))$, where $z = (s_2 + \alpha(s_1 + s_2))/(s_1 + \alpha(s_1 + s_2))$.

However, given these prices and the quadratic costs to quality, it is never optimal for the merged landlord to offer different quality of houses. Consider an improvement δ to the high quality house. This results in a increase in profits of

$$\Pi(r_1, r_2, s_1, s_2) = \Big[\bar{\theta} - \frac{\bar{\theta}}{2}\Big]\Big(\frac{\bar{\theta}(s_1 + \delta - s_2)}{2(1-z_\delta)} - \frac{(s_1+\delta)^2}{2}\Big) + \Big[\frac{\bar{\theta}}{2} - \frac{\bar{\theta}z_\delta(s_1 + \delta - s_2)}{2(1-z_\delta)(s_2 + \alpha(s_1 + s_2))}\Big]\Big(\frac{\theta z_\delta(s_1 + \delta - s_2)}{2(1-z_\delta)}$$

where $z_\delta = (s_2 + \alpha(s_1 + \delta + s_2))/(s_1 + \alpha(s_1 + \delta + s_2))$. Note that the demand for the high quality house does not vary with the quality of the neighborhood.Indeed the equilibrium prices the merged landlord will set will always have a difference of $\frac{\theta(s_1 - s_2)}{2}$. Hence, an increase in the quality of the high quality house does not increase demand for the high quality house. However, it does increase the demand for the low quality house by improving the neighborhood. With quadratic improvement costs, it is more expensive for the landlord to improve the quality of the high quality house, so the landlord will always choose to improve the low quality house until a point where the two qualities are equal.

Appendix A.4. Three house model: Owner Occupier

Consider now the impact of a third house in the neighborhood. Let this landlord be an owner occupier who has the same utility function as a renter but makes mortgage payments instead of rental payments:

$$U_o = \theta(s_o + n) - m \qquad \text{(Appendix 7)}$$

where s_o is the quality of owner occupier's house and m is the cost of mortgage payments. Assume that the owner occupier faces a borrowing constraint of γh where h is the value of the house. Let the value of the house be equal to the value of the property as a rental in perpetuity $h = r_i/i$, where i is the discount rate. For simplicity, I let the discount rate on the property equal to mortgage repayment rate. The owner occupier faces the same quadratic costs of improvement as other landlords, $c_o = s_o^2/2$.

Hence, the owner occupier chooses its level of home improvements to maximise its utility subject to its borrowing constraint $b \leq \gamma r_i/i$. Assuming the owner occupier has no mortgage initially, its utility is given by:

$$\theta(s_o + n) - \frac{is_o^2}{2}$$

and it maximises its utility where $s_o = \theta(1+\alpha)/i$. Assume that its θ is sufficiently high that the borrowing constraint is binding at the prevailing rental rate, r_i. That is, where $(\theta(1+\alpha))^2/2\gamma \geq r_i$. At this rate, the household will make improvements equal to $\sqrt{2\gamma r_i/i}$.

Consider the optimal behaviour of the merged landlord in this case. The landlord sets its price r_i in order to maximise:

$$\Pi(r_i, s_i) = \left[\bar{\theta} - \frac{r_i}{s_i(1+2\alpha) + \alpha(2\gamma r_i/i)^{1/2}}\right] r_i$$

Hence, it sets the rental price such that $t - \frac{r_i((4+8\alpha)s_i + 3\alpha(2\gamma r_i/i)^{1/2}}{2(s_i(1+2\alpha)+a(2\gamma r_i/i)^{1/2})^2} = 0$. In the first stage, it sets its quality to solve $\frac{(1+2\alpha)r_i^2}{(s_i(1+2\alpha)+\alpha(2\gamma r_i/i)^{1/2})^2} - s_i = 0$.

Appendix B. Ownership Matching

Each year the tax assessor for each county in the United States compiles a list of property ownership (tax parcel) in that county. These ownership lists contain details of the owner, their contact address, and details of the property, including its location and its appraisal value (land and improvements). The ownership information included in these tax records allows easy identification of owner-occupiers, but the ownership information may not identify the ultimate owner if the owner is an investor. In particular, many investors use locally registered limited liability companies (LLCs) to invest in real estate. The name of these LLCs may or may not be useful in identifying the ultimate owner. For example, American Homes 4 Rent (one of the largest financial investors in single family housing) owns property through at least 478 different LLCs with various names including AH4R I GA LLC and AMH 2014-I Borrower LLC. In order to correctly identify the type and size of each large investor in my sample, it is critical that these individual LLCs be correctly matched to an ultimate owner.In this Appendix, I describe the process I take to match these listed owners to ultimate parent.

First, I match properties using Exhibit 21.1 in SEC 10-K filings that includes each company's subsidiaries in that financial year. It is important to match these to an ultimate parent using both name and year, because name rarely changes post-merger. For example, Invitation Homes continues to use "SWAY 2014-1 Borrower GP LLC" as its subsidiary even though this LLC experienced two institutional mergers to be acquired by Invitation Homes (it originally belonged to Starwood Waypoint). This approach achieves a very comprehensive matching of subsidiaries to their ultimate parent where parent is US-listed.

However, private and non-US institutions are not required to release subsidiary details. I identify subsidiaries of these entities starting from my ownership data. First, I filter out those properties that have been identified as belonging to an owner-occupier (i.e. where the owner contact address is the same as the property address). Once owner-occupiers are removed, I sort all remaining owner-address pairs based on number of properties owned. I aim to find an ultimate owner for all those owner-address pairs with more than 50 properties under management.

I utilise OpenCorporates to assist in matching LLCs to ultimate owner. OpenCorporates contains the records of almost 200 million companies globally. I use OpenRefine to match records by name and jurisdiction to a record within the OpenCorporates database. Once I obtain a record identification number for each of the LLCs of interest, I use the OpenCorporates API to call the following information on each LLC: registered address, agent name, agent address, home company name, home company address, home company OpenCorporates URL, controlling entity name, controlling entity address, controlling entity URL.

Addresses alone are not useful without a database of ownership to match them to. I manually match 396 addresses to an ultimate parent. For example, the company "2015-3 IH2 BORROWER L.P" has a registered address of 1717 Main Street, Suite 2000, Dallas, Texas, 75201. This is one of the corporate offices of Invitation Homes. Therefore, I am able to match this obscurely-named LLC to an ultimate corporate parent.

However, this process can generate erroneous matches. For example, the address 2233 Peachtree Road, Suite 303, Atlanta, GA, 30309 belongs to a registered agent. Registered agents provide document collection services (especially for service of legal proceedings) for companies, so the address of a registered agent is uninformative in determining the ultimate owner. I collate a list of registered agents, lawyers, tax specialists, and other professional services firms to be excluded from the matching process. I cross-check the data to ensure that no address associated with more than 50 properties remains unidentified.

Finally, to ensure that I have captured all institutional owners, I search the Florida Division of Corporations. Florida is unique in providing corporations search based on address alone. Hence, I am able to identify the names of all subsidiaries operating in Florida whose contact address matches the corporate headquarters of an institutional investor in my sample. I am able to identify (or verify) the ultimate parent of a further 117 SFR LLCs using this database.

Appendix C. Census Matching

The Census database requires specific inputs including a street number, street name, and either city or zipcode to match a specific address to its corresponding entry in the Census database. One limitation of the tax parcel data for Fulton County is that only street number, street name, and street type were given for each tax parcel entry. Hence, this information alone was insufficient to match to an address in the Census database. To overcome this data limitation, I filtered for all those properties where the owner was identified as an owner-occupier in at least one year in the sample.. For these properties, the owner address (which contains both a city and zipcode) could be matched to an address in the Census database. This yielded XX exact matches to an entry in the Census database. For each of these properties, the Census information provided an estimated longitude and latitude, as well as the census tract number.

Next, I used these exact matches to find the census tract for other properties in my dataset. Census tracts are determined geographically, so it stands to reason that those properties that are geographically proximate would likely be in the same census tract. Using my existing matches, I identified all streets where there was a unique mapping between street name and type and census tract. I used this mapping to match all other properties on the same street to their imputed census tract.

There was not a unique mapping for every street in the sample. If the street was long or in a densely populated area, there could be multiple census tracts along the length of the street. In this case, I matches each address to the nearest neighbour for which census information was available. For example, I imputed that 6010 Spalding Drive, Sandy Springs, GA belonged to census tract 010108 from the information for 6018 Spalding Drive (rather than matching it to census tract 010107 that corresponded to 100 Spalding Drive, for example).

Appendix D. Screening for SFR mergers within CapitalIQ

I use Capital IQ to identify the largest mergers in the SFR market. Within Capital IQ, I screen for transactions (mergers and acquisitions) that contain the following features:

- Industry Classification (Target/Issuer): Diversified Real Estate Activities (Primary), Residential Building Operators or Lessors (Primary), Residential Property Managers (Primary), or Residential REITs;
- Transaction Types: Merger/Acquisition;
- Geographic Locations (Target/Issuer): United States and Canada (Primary);
- Transaction Status: Closed, Effective, Settled, or Successful;
- All Transactions Announced Date: [1/1/2015-12/31/2020];
- All Transactions Closed Date: [1/1/2015-12/31/2020]

Institutional investment in SFR real estate is a sufficiently new category of investment that it does not yet have its own industry classification within CapitalIQ. Hence, the industry identification is necessarily broad to ensure that SFR investors are not excluded from the pool of transactions. [43] This screen produces 528 potential transactions.

I identify transactions involving the firms I have previously identified as SFR owners. Three of the identified mergers are within the 20 largest transactions in the broader dataset: Invitation Homes' acquisition of Colony Starwood; Tricon American's acquisition of Silver Bay Realty Trust; and American Homes 4 Rent's acquisition of American Residential Properties. I identify the Colony American/Starwood Waypoint merger from commentary on another transaction, and I find value and announced/completion dates from press releases within SEC filings for Colony Starwood (as it became known).

[43] SFR investors could be categorised into any of the suggested industry classifications. Some (not all) are structured as residential REITs; some (e.g. Main Street Renewal or Altisource) are primarily property managers who own/are in partnership with owners of SFR real estate; all are in the business of leasing real estate to the public, but this may not be classified as their primary business if they fall into another category as above.

Appendix E. Institutional Investors and Arbitrage

Institutional investors may identify arbitrage opportunities, especially in situations of low market liquidity where there is a pricing gap in the market. Properties may be sold at lower than their fair market price if the seller is distressed, needs fast cash, or if the neighbourhood is quickly appreciating.

There are two possible mechanisms through which institutional investors may take advantage of arbitrage opportunities in the real estate market. The first is real estate speculation: it could be that institutional investors are better at identifying distressed sellers (or, conversely, neighbourhoods that are likely to improve) and choose to purchase from these individuals. This mechanism does not require the investor to make further improvements to the property following acquisition; it need only hold the property until prices increase. The second is house flipping: it could be that institutional investors purchase a number of properties in a neighbourhood with the intention to make improvements to the properties. These improvements improve the quality of the properties such that they may be resold at a higher price. This approach would be analogous to the "buy and build" strategy in private equity.

I do not find evidence in my data that institutional investors were able to purchase multiple distressed properties from a single seller in a single transaction. The inability to purchase portfolios of distressed assets was in large part a feature of the market. In 2009 and 2010, Fannie Mae and Freddie Mac, introduced the "First Look" program that gave home-owners and non-profit organisations the opportunity to bid on its REO properties before they became available to investors. In particular, the program restricted offers on all REO-owned properties to potential owner-occupiers (or non-profits) during each property's first 15 or 20 days on the market. [44] Given the average REO length is five months, these delays were non-trivial for investors. Perhaps most importantly, this programme excluded the opportunity for investors to purchase portfolios of distressed/foreclosed properties from the REO owners.

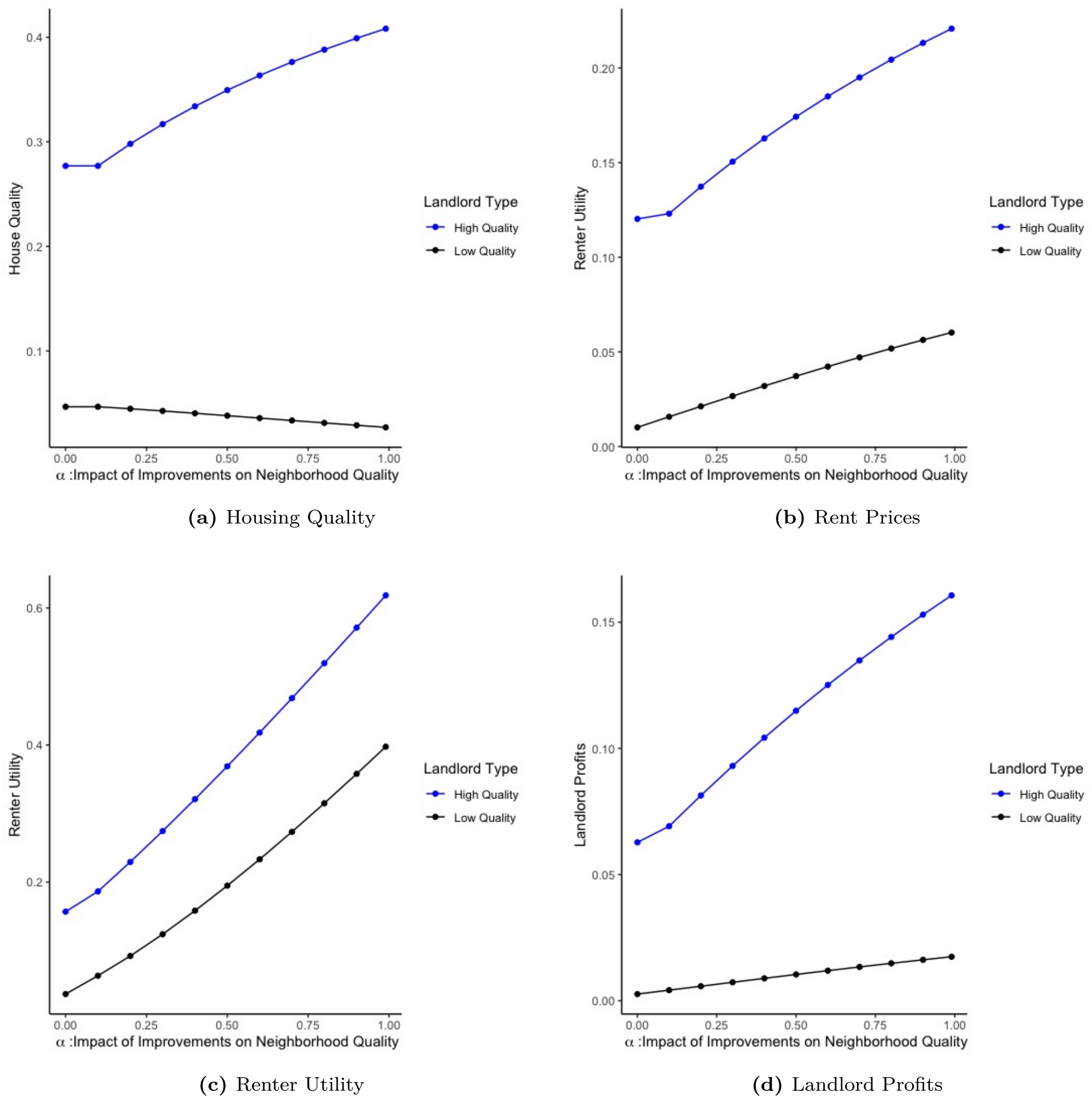
There was one notable exception to this. In 2012, Fannie Mae offered three portfolios of properties for sale to investors. [45]: These portfolios were:

- 699 properties in Central and Northeast, Southeast, and West Coast Florida
- 94 properties in Chicago, Illinois
- 970 properties in Arizona, California and Nevada

None of these portfolios included properties in Atlanta, Georgia, which suggests that institutional investors were not able to acquire portfolios of geographically proximate properties in my sample. The properties in each portfolio are sufficiently geographically disparate that it seems that these transactions cannot be used to evaluate the presence of geographic herding by or following institutional investors. Nevertheless, I have made a Freedom of Information Act request of Fannie Mae for the underlying transaction data. If the properties are more geographically concentrated than it would appear from the description, I may be able to use these transactions as to identify the impact of a sudden increase in institutional investment on neighbourhood improvements and permitting.

[44] Introductory documents on the First Look Initiative are available here and here

[45] Details of the portfolios and the offer process are available here



(a) Housing Quality

(b) Rent Prices

(c) Renter Utility

(d) Landlord Profits

Figure 9: Model Outputs for Duopoly Case with No Excess Demand
This figure presents the optimal choice of housing quality and rent prices from the housing model for different values of α (the impact of individual housing improvements on neighborhood quality). It also presents the profits of each landlord and the renter utility at each level of α.

Appendix G. Extra tables

Table A1: Tax Assessor Valuations around Mergers

(a) Total Valuations for Properties around Mergers

		Dependent variable: ln(Total Valuation)		
	Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
(1) Merged Landlord	Merged x Post x Treat	-0.044***	-0.016	0.001
		(-2.687)	(-0.924)	(0.809)
	Adjusted R^2	0.392	0.392	0.392
(2) Institutional Investor	SFR x Post x Treat	-0.004	0.055**	0.004***
		(-0.224)	(2.094)	(4.098)
	Adjusted R^2	0.393	0.393	0.393
All regressions	Tract x Year FE	Yes	Yes	Yes

(b) Tax Assessor Improvements Valuations around Mergers

		Dependent variable: ln(Improvements Valuation)		
	Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
(1) Merged Landlord	Merged x Post x Treat	-0.288***	0.030	0.001
		(-6.383)	(0.327)	(0.369)
	Adjusted R^2	0.275	0.275	0.275
(2) Institutional Investor	SFR x Post x Treat	-0.141	0.254*	0.020***
		(-1.216)	(1.713)	(3.755)
	Adjusted R^2	0.275	0.275	0.275
All regressions	Tract x Year FE	Yes	Yes	Yes

(c) Tax Assessor Home Condition Assessment around Mergers

		Dependent variable: Condition/Quality Grade		
	Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
(1) Merged Landlord	Merged x Post x Treat	0.005	-0.046	-0.001
		(0.066)	(-1.109)	(-1.425)
	Adjusted R^2	0.642	0.642	0.642
(2) Institutional Investor	SFR x Post x Treat	0.127***	0.067***	0.0005*
		(5.293)	(4.325)	(1.901)
	Adjusted R^2	0.642	0.642	0.642
All regressions	Tract x Year FE	Yes	Yes	Yes

This table presents estimates of difference-in-difference regressions of property valuations for institutional investor owned properties around the four mergers of institutional investors. The sample includes all properties in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The time period includes three years before each merger until four years after. The dependent variable for Panel A is the natural logarithm of the total tax assessor valuation, for Panel B is the natural logarithm of the tax assessor valuation of improvements (including house), and for Panel C is the tax assessor assessment of property condition/quality. I include results for (1) the merged landlord and (2) all institutional investors separately. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include tract x year fixed effects in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A2: Tax Assessor Valuations around Mergers

(a) Total Valuations for Merged Landlords' Properties around Mergers

Acquisition		*Dependent variable:* ln(Total Valuation)		
	Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
(1) American Homes 4 Rent	Institution x Post x Treat	-0.072**	-0.006	-0.001
		(-2.536)	(-0.383)	(-0.897)
	Adjusted R^2	0.396	0.396	0.396
(2) Colony/Starwood	Institution x Post x Treat	0.009	-0.031	-0.002***
		(0.210)	(-1.181)	(-3.646)
	Adjusted R^2	0.327	0.327	0.327
(3) Invitation Homes	Institution x Post x Treat	-0.013	-0.009	0.001
		(-0.311)	(-0.335)	(1.161)
	Adjusted R^2	0.345	0.345	0.345
(4) Tricon American	Institution x Post x Treat	-0.022**	-0.229***	-0.012***
		(-2.209)	(-4.759)	(-3.556)
	Adjusted R^2	0.297	0.297	0.297
All regressions	TractxYear FE	Yes	Yes	Yes

(b) Improvements Valuations for Properties around Mergers

Acquisition		*Dependent variable:* ln(Improvements (Home) Valuation)		
	Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
(1) American Homes 4 Rent	Merged x Post x Treat	-0.289***	0.033	0.0005
		(-6.122)	(1.642)	(0.256)
	Adjusted R^2	0.336	0.336	0.336
(2) Colony/Starwood	Merged x Post x Treat	0.457***	0.063*	-0.008***
		(5.270)	(1.949)	(-5.713)
	Adjusted R^2	0.303	0.303	0.303
(3) Invitation Homes	Merged x Post x Treat	-0.091	-0.010	0.002***
		(-1.453)	(-0.262)	(3.446)
	Adjusted R^2	0.290	0.290	0.290
(4) Tricon American	Merged x Post x Treat	-0.017	-1.318***	-0.047***
		(-0.496)	(-6.689)	(-3.774)
	Adjusted R^2	0.219	0.219	0.219
All regressions	TractxYear FE	Yes	Yes	Yes

This table presents estimates of difference-in-difference regressions of property valuations for institutional investor owned properties around the four mergers of institutional investors. The sample includes all properties in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The time period includes three years before each merger until four years after. The dependent variable for each regression is the natural logarithm of the tax assessor valuation. Panel A summarizes regression results for total property valuations of properties owned by a merged landlord following a merger, while Panel B summarizes the regression results for home/improvements valuations of properties owned by a merged landlord a merger. I disaggregate into each individual merger (merger identified by acquirer name in the first column). In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include tract x year in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A3: Change in property-level valuations around mergers

Dependent variable:	ln(Tax Assessor Valuation)		
Treatment Variable:	I (Δ Properties $>$ 0)	I (Δ Properties$>$ 10)	Δ Properties Count
AcquirerxPostxTreat	0.010	-0.025^{**}	-0.0001
	(0.031)	(0.012)	(0.0001)
TargetxPostxTreat	0.038	-0.023	0.0001
	(0.075)	(0.015)	(0.0001)
Post	0.0001	-0.0003^{***}	-0.0001
	(0.0001)	(0.0001)	(0.0002)
Treat	0.0001^{*}	0.0003^{***}	0.00002^{**}
	(0.0001)	(0.0001)	(0.00001)
PostxTreat	-0.0001	0.0005^{***}	0.00001
	(0.0001)	(0.0001)	(0.00001)
Acquirer	-0.035	-0.083^{***}	-0.082^{***}
	(0.042)	(0.016)	(0.009)
AcquirerxPost	-0.020	0.012	-0.007
	(0.030)	(0.011)	(0.005)
AcquirerxTreat	-0.041	0.010	0.0002
	(0.043)	(0.018)	(0.0001)
Target	0.055	-0.055^{***}	-0.059^{***}
	(0.066)	(0.015)	(0.011)
TargetxPost	-0.052	0.006	-0.022^{***}
	(0.075)	(0.014)	(0.007)
TargetxTreat	-0.120^{*}	-0.010	-0.0001
	(0.067)	(0.018)	(0.0002)
Census tract x Year FE	Yes	Yes	Yes
Adjusted R^2	0.615	0.615	0.615
Observations	16,521,800	16,521,800	16,521,800

This table presents estimates of difference-in-difference regressions of property valuations. The sample includes the property valuations of properties in merged neighbourhoods, as well as properties in neighbourhoods where at least one acquiring firm owned a property prior to the acquisition. The dependent variable is the natural logarithm of the tax assessor (total) valuation of each property. In column 1, Treat is a binary variable that takes the value of 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. MergerLandlord is a binary variable that equals 1 if the property is owned by either the acquirer or the target firm. I include census tract x year fixed effects in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A4: All Applications for Loans for Home Improvements (with controls)

Dependent variable:	ln(Mean Value of Improvement Applications)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	4.131***	4.289***	4.290***
	(36.328)	(44.885)	(42.874)
Treat	-0.127***	-0.147***	-0.011***
	(-2.924)	(-3.022)	(-5.286)
PostxTrans	0.292***	0.172***	0.007**
	(3.863)	(2.692)	(2.242)
LagHPI	0.004***	0.004***	0.004***
	(4.143)	(3.892)	(3.903)
One_Four_Homes	0.0003	0.0003	0.0003
	(0.920)	(0.886)	(0.934)
log(Median_Income)	16.845***	16.901***	16.863***
	(27.475)	(27.018)	(26.908)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,739	3,739	3,739
Adjusted R^2	0.899	0.899	0.899

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes all years from 2010-2021. The dependent variable is the natural logarithm of 1 + the number of non-white applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage applications in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A5: Owner Occupier Applications for Loans for Home Improvements (with controls)

Dependent variable:	ln(Mean Value of Improvement Applications)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	4.070***	4.239***	4.236***
	(36.306)	(44.720)	(42.665)
Treat	-0.139***	-0.149***	-0.012***
	(-3.225)	(-3.052)	(-5.428)
PostxTrans	0.312***	0.181***	0.008**
	(4.127)	(2.797)	(2.526)
LagHPI	0.004***	0.004***	0.004***
	(4.002)	(3.717)	(3.742)
One_Four_Homes	0.0002	0.0002	0.0002
	(0.678)	(0.654)	(0.701)
log(Median_Income)	17.054***	17.118***	17.078***
	(27.953)	(27.450)	(27.365)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,738	3,738	3,738
Adjusted R^2	0.898	0.898	0.898

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes all years from 2010-2021. The dependent variable is the natural logarithm of 1 + the number of non-white applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage applications in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A6: Investor Applications for Loans for Home Improvements (with controls)

Dependent variable:	ln(Mean Value of Improvement Applications)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	4.439***	4.523***	4.565***
	(20.085)	(23.939)	(23.308)
Treat	0.002	0.004	-0.003
	(0.021)	(0.041)	(-0.847)
PostxTrans	0.102	-0.065	-0.008
	(0.737)	(-0.453)	(-1.313)
LagHPI	0.007***	0.007***	0.007***
	(3.655)	(3.556)	(3.531)
One_Four_Homes	0.0004	0.0004	0.0004
	(0.612)	(0.642)	(0.645)
log(Median_Income)	18.637***	18.663***	18.599***
	(14.523)	(14.438)	(14.295)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	2,382	2,382	2,382
Adjusted R^2	0.869	0.869	0.869

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes all years from 2010-2021. The dependent variable is the natural logarithm of 1 + the number of non-white applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage applications in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A7: Mean Value of All Loans Originations for Home Improvements (with controls)

Dependent variable:	ln(Mean Value of Improvement Originations)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	4.025***	4.241***	4.244***
	(35.593)	(44.183)	(42.168)
Treat	-0.197***	-0.191***	-0.013***
	(-3.976)	(-3.265)	(-4.308)
PostxTrans	0.400***	0.251***	0.010**
	(4.583)	(2.881)	(2.145)
LagHPI	0.004***	0.003***	0.003***
	(3.134)	(2.786)	(2.770)
One_Four_Homes	-0.00001	-0.00002	0.00001
	(-0.033)	(-0.038)	(0.018)
log(Median_Income)	17.147***	17.237***	17.211***
	(24.708)	(24.311)	(24.247)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,608	3,608	3,608
Adjusted R^2	0.886	0.885	0.885

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes all years from 2010-2021. The dependent variable is the natural logarithm of 1 + the number of non-white applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage applications in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A8: Owner Occupier Loan Originations for Home Improvements (with controls)

Dependent variable:	ln(Mean Value of Improvement Applications)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	3.933***	4.160***	4.154***
	(36.078)	(44.614)	(42.493)
Treat	-0.208***	-0.214***	-0.014***
	(-4.135)	(-3.634)	(-4.831)
PostxTrans	0.430***	0.300***	0.013***
	(4.868)	(3.364)	(2.845)
LagHPI	0.004***	0.004***	0.004***
	(3.240)	(2.880)	(2.883)
One_Four_Homes	-0.0002	-0.0002	-0.0002
	(-0.585)	(-0.576)	(-0.517)
log(Median_Income)	17.545***	17.636***	17.611***
	(24.822)	(24.411)	(24.364)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,566	3,566	3,566
Adjusted R^2	0.883	0.883	0.883

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes all years from 2010-2021. The dependent variable is the natural logarithm of 1 + the number of non-white applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage applications in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A9: Mean Value of Loan Originations for Home Improvements by Investors (with controls)

Dependent variable:	ln(Mean Value of Improvement Originations)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	3.273***	3.215***	3.366***
	(10.040)	(11.314)	(11.395)
Treat	0.080	0.218	0.007
	(0.574)	(1.485)	(1.117)
PostxTrans	-0.212	-0.443	-0.038***
	(-0.860)	(-1.362)	(-2.817)
LagHPI	0.002	0.002	0.002
	(0.560)	(0.537)	(0.441)
One_Four_Homes	0.002**	0.002**	0.002**
	(2.033)	(2.118)	(2.101)
log(Median_Income)	24.675***	24.695***	24.586***
	(11.569)	(11.611)	(11.638)
LagInvestorsApprovals	0.035***	0.035***	0.034***
	(3.709)	(3.687)	(3.497)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	1,027	1,027	1,027
Adjusted R^2	0.869	0.869	0.870

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes all years from 2010-2021. The dependent variable is the natural logarithm of 1 + the number of non-white applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage applications in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A10: Investor Home Loan Applications (with controls)

Dependent variable:	ln(Investor Loan Applications)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	0.047*	0.061***	0.057**
	(1.808)	(2.771)	(2.554)
Treat	-0.0005	0.032**	0.001
	(-0.034)	(2.157)	(0.670)
PostxTrans	0.014	-0.031	-0.0003
	(0.609)	(-1.184)	(-0.285)
LagHPI	-0.00005	-0.0001	-0.0001
	(-0.142)	(-0.271)	(-0.209)
One_Four_Homes	0.0001	0.0001	0.0001
	(1.130)	(1.175)	(1.143)
log(Median_Income)	0.544***	0.559***	0.553***
	(3.078)	(3.154)	(3.116)
LagInvestorsApprovals	0.033***	0.033***	0.033***
	(18.967)	(18.859)	(18.892)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.767	0.767	0.767

This table presents estimates of difference-in-difference regressions of mortgage applications by investors around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before each merger until four years after. The dependent variable is the natural logarithm of 1 + the number of investor applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the lag of the house price index, the lag of investor approvals (as a proxy for number of investment properties), the tract median incomes, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A11: Investor Home Loan Approvals (with controls)

Dependent variable:	ln(Investor Loan Originations)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	0.061**	0.062**	0.056**
	(2.150)	(2.581)	(2.299)
Treat	0.003	0.021	-0.00003
	(0.172)	(1.201)	(-0.024)
PostxTrans	0.005	0.008	0.001
	(0.216)	(0.258)	(0.795)
LagHPI	-0.0004	-0.0004	-0.0004
	(-1.226)	(-1.243)	(-1.178)
One_Four_Homes	0.0001	0.0001	0.0001
	(1.155)	(1.153)	(1.155)
log(Median_Income)	0.577***	0.582***	0.578***
	(3.039)	(3.074)	(3.055)
LagInvestorsApprovals	0.042***	0.042***	0.042***
	(16.319)	(16.300)	(16.334)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.712	0.712	0.712

This table presents estimates of difference-in-difference regressions of mortgage applications by investors around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before each merger until four years after. The dependent variable is the natural logarithm of 1 + the number of investor applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the lag of the house price index, the lag of investor approvals (as a proxy for number of investment properties), the tract median incomes, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A12: Owner Occupier Permit Activity Around Mergers

Dependent variable:	ln(Permits Issued)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	0.004	0.462***	0.320**
	(0.022)	(3.481)	(2.148)
Treat	-0.253**	-0.033	-0.013*
	(-2.257)	(-0.326)	(-1.922)
Post x Treat	0.584***	0.277	0.033***
	(3.089)	(1.661)	(2.671)
LagHPI	-0.018***	-0.019***	-0.018***
	(-8.160)	(-8.474)	(-8.361)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	965	965	965
Adjusted R^2	0.433	0.424	0.429

This table presents estimates of difference-in-difference regressions of building permits issued for owner occupier owners around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before each merger until four years after. The dependent variable is the natural logarithm of 1 + the number of owner occupier permits issued in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A13: Small Investor Permit Activity Around Mergers

Dependent variable:	ln(Permits Issued)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.085	0.201**	0.118
	(-0.519)	(2.095)	(1.113)
Treat	-0.174*	-0.055	-0.008
	(-1.893)	(-0.655)	(-1.554)
PostxTrans	0.388**	0.256*	0.023**
	(2.589)	(1.888)	(2.224)
LagHPI	-0.010***	-0.011***	-0.011***
	(-5.480)	(-5.812)	(-5.729)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	965	965	965
Adjusted R^2	0.362	0.359	0.361

This table presents estimates of difference-in-difference regressions of building permits issued for small investor owners around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before each merger until four years after. The dependent variable is the natural logarithm of 1 + the number of small investor permits issued in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A14: Large Investor Permit Activity Around Mergers

Dependent variable:	ln(Permits Issued)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	0.487	0.537***	0.587**
	(1.512)	(2.672)	(2.587)
Treat	0.026	0.068	0.012
	(0.148)	(0.435)	(1.121)
PostxTrans	0.062	0.042	-0.007
	(0.234)	(0.166)	(-0.358)
LagHPI	-0.010***	-0.011***	-0.011***
	(-2.956)	(-3.029)	(-3.050)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	965	965	965
Adjusted R^2	0.520	0.521	0.521

This table presents estimates of difference-in-difference regressions of building permits issued for large investor owners around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before each merger until four years after. The dependent variable is the natural logarithm of 1 + the number of large investor permits issued in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression, and the lag of the house price index. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A15: SFR Investor Permit Activity Around Mergers

Dependent variable:	ln(Permits Issued)		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	0.048	0.094	0.100
	(0.844)	(1.251)	(1.251)
Treat	-0.030	-0.029	-0.0004
	(-1.139)	(-0.672)	(-0.143)
PostxTrans	0.065	0.043	0.001
	(1.324)	(0.606)	(0.187)
LagHPI	-0.001	-0.001	-0.001
	(-1.180)	(-1.174)	(-1.207)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	965	965	965
Adjusted R^2	0.081	0.081	0.081

This table presents estimates of difference-in-difference regressions of building permits issued for large investor owners around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before each merger until four years after. The dependent variable is the natural logarithm of 1 + the number of large investor permits issued in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression, and the lag of the house price index. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A16: Mortgage applications by race/ethnicity around mergers: 2010-2021

Dependent Variable				
	Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
(1) Black/African American	Post x Treat	0.128***	0.108**	0.004***
		(2.815)	(2.557)	(2.949)
	Adjusted R^2	0.764	0.763	0.763
(2) White	Post x Treat	0.105**	0.149***	0.007***
		(2.394)	(3.295)	(3.583)
	Adjusted R^2	0.897	0.897	0.897
(3)Latino/Hispanic	Post x Treat	0.236***	0.222***	0.009***
		(5.381)	(5.255)	(3.855)
	Adjusted R^2	0.670	0.668	0.669
(4) Asian	Post x Treat	0.081*	0.151***	0.006***
		(1.910)	(3.049)	(3.332)
	Adjusted R^2	0.753	0.753	0.753
(5) Native American	Post x Treat	−0.004	0.019	0.0004
		(-0.241)	(1.264)	(0.662)
	Adjusted R^2	0.138	0.138	0.138
(6) Mixed Race/Ethnicity	Post x Treat	0.030	0.029	0.002
		(0.890)	(0.735)	(1.347)
	Adjusted R^2	0.530	0.530	0.530
(7) Non-White	Post x Treat	0.124***	0.127***	0.005***
		(3.029)	(3.351)	(3.911)
	Adjusted R^2	0.755	0.755	0.755
All regressions	CountyxYear FE	Yes	Yes	Yes
All regressions	Tract FE	Yes	Yes	Yes
All regressions	Observations	6,512	6,512	6,512

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The time period includes all years from 2010-2021. The dependent variable for each regression is the natural logarithm of 1 + the application count in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A17: Mortgage originations by race/ethnicity around mergers: 2010-2021

Dependent Variable				
	Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
(1) Black/African American	Post x Treat	0.126***	0.100**	0.005***
		(2.659)	(2.090)	(2.715)
	Adjusted R^2	0.669	0.668	0.668
(2) White	Post x Treat	0.015	0.040	0.001
		(0.298)	(0.905)	(0.891)
	Adjusted R^2	0.866	0.866	0.866
(3)Latino/Hispanic	Post x Treat	0.200***	0.157***	0.006***
		(4.835)	(3.378)	(2.990)
	Adjusted R^2	0.611	0.610	0.610
(4) Asian	Post x Treat	0.071*	0.147***	0.006***
		(1.731)	(2.935)	(3.073)
	Adjusted R^2	0.707	0.708	0.708
(5) Native American	Post x Treat	0.011	-0.002	-0.0002
		(1.126)	(-0.178)	(-0.483)
	Adjusted R^2	0.083	0.082	0.082
(6) Mixed Race/Ethnicity	Post x Treat	-0.050	-0.082**	-0.002
		(-1.617)	(-2.476)	(-1.203)
	Adjusted R^2	0.472	0.473	0.472
(7) Non-White	Post x Treat	0.113**	0.119***	0.005***
		(2.455)	(2.878)	(3.013)
	Adjusted R^2	0.691	0.691	0.691
All regressions	CountyxYear FE	Yes	Yes	Yes
All regressions	Tract FE	Yes	Yes	Yes
All regressions	Observations	6,512	6,512	6,512

This table presents estimates of difference-in-difference regressions of mortgage originations by race/ethnicity around the four mergers of institutional investors. The sample includes the originations in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The time period includes all years from 2010-2021. The dependent variable for each regression is the natural logarithm of 1 + the origination count for each race/ethnicity group in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A18: Black/African American Mortgage Applications (with controls)

Dependent variable:	Black/African American Applications		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.020	1.070**	0.496
	(-0.030)	(2.186)	(0.969)
Treat	-1.335**	-1.754**	-0.146***
	(-2.543)	(-2.243)	(-3.447)
Post x Treat	2.541***	2.839**	0.221***
	(2.696)	(2.141)	(3.248)
LagHPI	-0.030***	-0.032***	-0.029***
	(-2.842)	(-2.998)	(-2.813)
One_Four_Homes	0.002	0.002	0.002
	(0.478)	(0.437)	(0.491)
log(Median_Income)	13.526***	13.777***	13.427***
	(3.196)	(3.195)	(3.170)
All_Approvals_Count	0.331***	0.335***	0.332***
	(7.655)	(7.784)	(7.730)
LagInvestorsApprovals	0.134***	0.131***	0.135***
	(3.279)	(3.084)	(3.206)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.781	0.780	0.783

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years prior to the transaction until four years after. The dependent variable is the number of Black/African American applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage applications in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A19: White Mortgage Applications (with controls)

Dependent variable:	White Applications		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	1.798**	1.756***	2.034***
	(2.390)	(3.177)	(3.567)
Treat	0.341	1.419***	0.080***
	(0.680)	(3.053)	(3.712)
Post x Treat	-0.814	-2.607***	-0.149***
	(-0.964)	(-3.189)	(-4.029)
LagHPI	-0.019	-0.021	-0.022*
	(-1.504)	(-1.632)	(-1.695)
One_Four_Homes	0.001	0.001	0.001
	(0.141)	(0.200)	(0.157)
log(Median_Income)	-29.578***	-29.321***	-29.337***
	(-5.615)	(-5.636)	(-5.634)
All_Approvals_Count	0.521***	0.522***	0.523***
	(16.698)	(16.973)	(16.973)
LagInvestorsApprovals	-0.030	-0.032	-0.034
	(-0.822)	(-0.862)	(-0.907)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.958	0.958	0.958

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years prior to each merger until four years after. The dependent variable is the number of white applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage applications in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A20: Latino/Hispanic Mortgage Applications (with controls)

Dependent variable:	Latino/Hispanic Applications		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.409	0.128	0.041
	(-1.324)	(0.481)	(0.149)
Treat	-0.660***	-0.724**	-0.029*
	(-3.305)	(-2.311)	(-1.746)
Post x Treat	1.295***	1.514***	0.070**
	(3.648)	(2.820)	(2.429)
LagHPI	0.012***	0.011**	0.011**
	(2.627)	(2.481)	(2.528)
One_Four_Homes	-0.001	-0.001	-0.001
	(-0.345)	(-0.383)	(-0.318)
log(Median_Income)	8.224***	8.382***	8.494***
	(4.021)	(4.093)	(4.151)
All_Approvals_Count	0.106***	0.108***	0.108***
	(11.410)	(11.749)	(11.736)
LagInvestorsApprovals	-0.023*	-0.025*	-0.025*
	(-1.656)	(-1.746)	(-1.711)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.658	0.658	0.658

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before each merger until four years after. The dependent variable is the number of Latino/Hispanic applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage approvals in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A21: Asian Mortgage Applications (with controls)

Dependent variable:	Asian Applications		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.017	-0.460	-0.407
	(-0.040)	(-1.444)	(-1.280)
Treat	0.356	-0.372	0.002
	(1.468)	(-0.879)	(0.176)
Post x Treat	-0.543	0.583	0.008
	(-1.269)	(0.976)	(0.380)
LagHPI	0.002	0.003	0.003
	(0.253)	(0.493)	(0.431)
One_Four_Homes	0.001	0.001	0.001
	(0.751)	(0.690)	(0.726)
log(Median_Income)	-3.961	-4.285	-4.130
	(-1.220)	(-1.328)	(-1.282)
All_Approvals_Count	0.182***	0.180***	0.180***
	(7.722)	(7.636)	(7.631)
LagInvestorsApprovals	-0.017	-0.015	-0.015
	(-0.801)	(-0.693)	(-0.719)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.815	0.815	0.815

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years prior to each merger until four years after. The dependent variable is the number of Asian applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage approvals in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A22: Mixed Race/Ethnicity Mortgage Applications (with controls)

Dependent variable:	Mixed Race/Ethnicity Applications		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	0.047	-0.110	-0.072
	(0.305)	(-0.857)	(-0.544)
Treat	0.196**	0.244***	0.013***
	(2.304)	(3.637)	(4.188)
Post x Treat	-0.370***	-0.420***	-0.023***
	(-2.895)	(-3.387)	(-3.930)
LagHPI	0.008***	0.008***	0.008***
	(3.945)	(4.127)	(4.057)
One_Four_Homes	-0.001	-0.001	-0.001
	(-1.102)	(-1.070)	(-1.128)
log(Median_Income)	2.439***	2.401***	2.400**
	(2.628)	(2.601)	(2.591)
All_Approvals_Count	0.030***	0.029***	0.029***
	(8.349)	(8.249)	(8.291)
LagInvestorsApprovals	0.006	0.006	0.006
	(0.729)	(0.775)	(0.748)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.516	0.515	0.516

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years prior to each merger until four years after. The dependent variable is the number of mixed race/ethnicity applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage approvals in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A23: Non-White Mortgage Applications (with controls)

Dependent variable:	Non-White Applications		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.378	0.712	0.125
	(-0.540)	(1.270)	(0.215)
Treat	-1.526***	-2.771***	-0.168***
	(-3.194)	(-4.239)	(-5.352)
Post x Treat	3.102***	4.790***	0.290***
	(3.620)	(4.426)	(5.597)
LagHPI	-0.014	-0.014	-0.013
	(-1.200)	(-1.242)	(-1.085)
One_Four_Homes	0.003	0.003	0.003
	(0.696)	(0.614)	(0.705)
log(Median_Income)	19.305***	19.352***	19.263***
	(3.794)	(3.816)	(3.824)
All_Approvals_Count	0.628***	0.631***	0.628***
	(16.163)	(16.325)	(16.261)
LagInvestorsApprovals	0.091*	0.089*	0.093*
	(1.891)	(1.813)	(1.909)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.868	0.869	0.870

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before the merger until four years after. The dependent variable is the number of non-white applications in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage approvals in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A24: Black/African American Mortgage Originations (with controls)

Dependent variable:	Black/African American Originations		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.271	0.140	-0.172
	(-0.637)	(0.440)	(-0.519)
Treat	-0.565*	-0.863*	-0.080***
	(-1.700)	(-1.893)	(-3.241)
Post x Treat	1.037*	1.353*	0.114***
	(1.751)	(1.781)	(2.910)
LagHPI	-0.019***	-0.019***	-0.018***
	(-2.780)	(-2.917)	(-2.722)
One_Four_Homes	0.002	0.002	0.002
	(0.821)	(0.781)	(0.842)
log(Median_Income)	9.070***	9.127***	8.894***
	(3.272)	(3.271)	(3.225)
All_Approvals_Count	0.212***	0.213***	0.211***
	(7.479)	(7.626)	(7.553)
LagInvestorsApprovals	0.075***	0.074***	0.076***
	(2.776)	(2.649)	(2.750)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.745	0.745	0.748

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years prior to the transaction until four years after. The dependent variable is the number of Black/African American originations in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage applications in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A25: White Mortgage Originations (with controls)

Dependent variable:	White Mortgage Originations		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.771	-0.997***	-0.768**
	(-1.600)	(-2.827)	(-2.073)
Treat	0.495	1.213***	0.072***
	(1.583)	(3.793)	(4.947)
Post x Treat	-0.963*	-2.111***	-0.122***
	(-1.764)	(-3.979)	(-4.895)
LagHPI	-0.004	-0.004	-0.005
	(-0.465)	(-0.541)	(-0.632)
One_Four_Homes	-0.0004	-0.0002	-0.0004
	(-0.161)	(-0.092)	(-0.151)
log(Median_Income)	-11.346***	-11.235***	-11.203***
	(-3.834)	(-3.847)	(-3.838)
All_Approvals_Count	0.390***	0.390***	0.391***
	(17.425)	(17.688)	(17.717)
LagInvestorsApprovals	-0.067***	-0.067***	-0.069***
	(-2.870)	(-2.886)	(-2.949)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.965	0.965	0.965

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years prior to each merger until four years after. The dependent variable is the number of white originations in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage approvals in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A26: Latino/Hispanic Mortgage Originations (with controls)

Dependent variable:	Latino/Hispanic Mortgage Originations		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.587***	-0.310*	-0.360*
	(-2.868)	(-1.743)	(-1.969)
Treat	-0.359**	-0.372*	-0.012
	(-2.528)	(-1.728)	(-1.159)
Post x Treat	0.691***	0.858**	0.039**
	(2.822)	(2.341)	(2.159)
LagHPI	0.008**	0.007**	0.008**
	(2.554)	(2.482)	(2.512)
One_Four_Homes	-0.001	-0.001	-0.001
	(-0.575)	(-0.605)	(-0.547)
log(Median_Income)	7.770***	7.853***	7.940***
	(5.366)	(5.457)	(5.518)
All_Approvals_Count	0.073***	0.074***	0.074***
	(11.306)	(11.675)	(11.603)
LagInvestorsApprovals	-0.017*	-0.017*	-0.017*
	(-1.732)	(-1.791)	(-1.770)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.654	0.654	0.654

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before each merger until four years after. The dependent variable is the number of Latino/Hispanic loan originations in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage originations in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A27: Asian Mortgage Originations (with controls)

Dependent variable:	Asian Mortgage Originations		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.301	-0.479*	-0.480*
	(-0.995)	(-1.950)	(-1.964)
Treat	0.021	-0.339	-0.004
	(0.129)	(-1.110)	(-0.409)
Post x Treat	-0.109	0.612	0.020
	(-0.386)	(1.459)	(1.174)
LagHPI	0.002	0.003	0.003
	(0.466)	(0.639)	(0.607)
One_Four_Homes	0.001	0.001	0.001
	(0.604)	(0.537)	(0.581)
log(Median_Income)	-2.796	-2.953	-2.845
	(-1.270)	(-1.350)	(-1.300)
All_Approvals_Count	0.128***	0.127***	0.127***
	(7.488)	(7.425)	(7.424)
LagInvestorsApprovals	-0.014	-0.013	-0.013
	(-0.909)	(-0.830)	(-0.841)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.804	0.804	0.804

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years prior to each merger until four years after. The dependent variable is the number of Asian loan originations in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage originations in the tract, the lag of investor mortgage originations (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A28: Mixed Race/Ethnicity Mortgage Originations (with controls)

Dependent variable:	Mixed Race/Ethnicity Mortgage Originations		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post	-0.059	-0.180**	-0.152*
	(-0.556)	(-2.083)	(-1.734)
Treat	0.161***	0.203***	0.012***
	(2.773)	(4.029)	(5.287)
Post x Treat	-0.299***	-0.368***	-0.019***
	(-3.166)	(-4.156)	(-4.989)
LagHPI	0.005***	0.005***	0.005***
	(2.970)	(3.093)	(3.029)
One_Four_Homes	-0.001**	-0.001**	-0.001**
	(-2.109)	(-2.058)	(-2.139)
log(Median_Income)	2.572***	2.544***	2.545***
	(3.635)	(3.615)	(3.601)
All_Approvals_Count	0.022***	0.022***	0.022***
	(9.152)	(9.008)	(9.046)
LagInvestorsApprovals	0.002	0.003	0.003
	(0.453)	(0.507)	(0.480)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.520	0.519	0.520

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years prior to each merger until four years after. The dependent variable is the number of mixed race/ethnicity mortgage originations in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage originations in the tract, the lag of investor approvals (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table A29: Non-White Mortgage Originations (with controls)

Dependent variable:	Non-White Applications		
Treatment Variable:	I (Δ Properties > 0)	I (Δ Properties > 20)	Δ Properties Count
Post x Treat	1.498***	2.669***	0.165***
	(2.797)	(4.562)	(6.321)
Post	-1.172**	-0.711*	-1.058***
	(-2.445)	(-1.903)	(-2.771)
Treat	-0.831***	-1.484***	-0.092***
	(-2.755)	(-4.095)	(-6.047)
LagHPI	-0.007	-0.007	-0.006
	(-0.974)	(-0.981)	(-0.824)
One_Four_Homes	0.002	0.002	0.002
	(0.668)	(0.583)	(0.669)
log(Median_Income)	15.314***	15.287***	15.243***
	(4.661)	(4.707)	(4.713)
All_Approvals_Count	0.422***	0.423***	0.421***
	(16.842)	(17.072)	(16.971)
LagInvestorsApprovals	0.041	0.041	0.043
	(1.191)	(1.165)	(1.237)
County x Year FE	Yes	Yes	Yes
Tract FE	Yes	Yes	Yes
Observations	3,740	3,740	3,740
Adjusted R^2	0.871	0.872	0.873

This table presents estimates of difference-in-difference regressions of mortgage applications by race/ethnicity around the four mergers of institutional investors. The sample includes the applications in all neighbourhoods where the acquirer and target both owned properties, as well as neighbourhoods in which at least one acquiring firm owned a property prior to the acquisition. The sample includes from three years before the merger until four years after. The dependent variable is the number of non-white mortgage originations in each tract. In column 1, Treat is a binary variable that equals 1 if the acquirer gained at least one additional property in a neighbourhood as a result of the merger. In column 2, Treat is a binary variable that equals 1 if the acquirer gained at least ten properties in the neighbourhood following the merger. In column 3, Treat is the count of properties the acquirer gained in a neighbourhood following the acquisition. I include county x year and tract fixed effects in each regression. I also include a variety of controls including the total number of mortgage originations in the tract, the lag of investor loan originations (as a proxy for number of investment properties), the tract population, the lag of the house price index, and the number of one-to-four family homes in the tract. I report t-statistics using standard errors clustered by census tract in parenthesis. *p<0.1; **p<0.05; ***p<0.01