Single-Family REITs and Local Housing Markets*

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July 28, 2025

Abstract

We study the rise of single-family real estate investment trusts (SF-REITs) using a novel property-level dataset that we construct. SF-REITs tend to buy homes in neighborhoods near city centers, where housing supply is relatively elastic and residents are on the lower rungs of the homeownership ladder. Using a spatial differences approach, we find that SF-REIT growth modestly raises prices and increases overall housing supply, with individual ownership rising at a similar rate. However, we find no evidence that SF-REITs reduce house purchase financing accessibility—mortgage approval rates and borrower credit profiles remain unchanged. Overall, institutional landlords have had a limited impact on access to homeownership.

Keywords: REITs, House Prices, Homeownership, Institutional Investors

*We thank our discussants Yun Joo An, Walter D'lima, Tingyu Zhou, and participants in various seminars and conferences for their comments. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Nothing in the text should be construed as an endorsement of any organization or its products or services. No statements here should be treated as legal advice. Any errors or omissions are the responsibility of the authors.

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1 Introduction

Barriers to homeownership have increased significantly since the 2008 Great Recession. Home prices have more than doubled between 2010 and 2021.[1] Some estimates suggest that inventory has not kept pace with demand and that the U.S. has at least a one million unit shortfall.[2] More home buyers find it difficult to obtain a mortgage (see e.g., D'Acunto and Rossi, 2022). Policymakers and the popular press frequently suggest that institutional investors (i.e., "Wall Street") are a leading contributor to the "affordability crisis" by crowding out individual home buyers.[3] Though institutional investment can benefit economic activity, a growing body of research documents ways in which institutional investors can negatively affect households in other settings.[4] Institutional and small-scale investors can also affect household well-being by shaping housing markets, for example, through their effects on rental prices (see e.g., Gurun et al., 2023). Nonetheless, there is relatively little empirical research on the rise of institutional ownership in single-family housing and its effects on local housing market accessibility.

In this paper, we explore the growth of single-family real estate investment trusts (SF-REITs) and their effects on local housing markets. Relative to REITs more broadly, we view the growth of SF-REITs as a "shock" to a housing segment that has not previously faced competition from institutional landlords. Institutional landlords have historically operated in multi-family housing where they have a comparative advantage of scale. Yet the recent entry of SF-REITs into single-family residential neighborhoods can potentially affect market characteristics, such as home-purchase accessibility and affordability.

To benchmark our analysis, the marginal household should be indifferent between owning and occupying housing or renting from landlords. Moreover, homeowners and renters can hedge differences between their asset returns and their exposure to idiosyncratic shocks by purchasing equity in REITs. As such, the price and allocation of housing should be determined by its best economic use. Ownership composition should not affect market outcomes such as prices, supply, and credit access.

Realistically, however, SF-REITs' home purchasing and ownership might shape local housing market outcomes because of housing market frictions and the fundamental differences between institutional and individual home buyers. First, SF-REITs obtain financing

[1] See e.g., the S&P CoreLogic Case-Shiller U.S. National Home Price Index.

[2] See e.g., Moody's Analytics article (click here for the link).

[3] See e.g., the "Stop Predatory Investing Act" proposed by the U.S. Senate and numerous articles in major media (click here for the link).

[4] For example, research shows negative effects on individuals' employment, healthcare, and consumption (see, e.g., Flynn and Ghent, 2022; Chodorow-Reich et al., 2021; Gupta et al., 2024; Fracassi et al., 2022).

at the fund level through capital markets whereas household buyers cannot easily raise equity and are subject to collateral constraints. Second, institutional buyers treat properties as financial assets whereas homeowners might derive utility from consumption of housing.[5] Finally, SF-REITs are subject to regulatory requirements that encourage long-term holding of residential assets, unlike individual owners who face no restrictions on when they can sell. These institutional features suggest that the entry of SF-REITs could plausibly affect local housing dynamics in ways that differ from traditional homeownership.

We contribute to the understanding of the effects of institutional real estate investors by constructing a novel dataset that identifies and tracks the specific properties held by different SF-REITs. Our dataset construction is validated by the locations named in SF-REITs' financial statements, which focus on 16 states that comprise the majority of SF-REIT property holdings in the U.S. Then, we use these data to measure SF-REIT holdings at the ZIP code level between 2010 and 2021. SF-REITs frequently acquire properties through satellite entities, making it difficult for researchers to construct data sets such as ours (see the description of our methodology in Appendix A1).

Our empirical analysis begins by examining where SF-REITs have expanded their property holdings. Given the precision of our identification algorithm, we focus initially on the three largest SF-REITs—Invitation Homes (INVH), American Homes 4 Rent (AMH), and Tricon—which together account for roughly 90% of the SF-REIT market. We then broaden the analysis to include additional SF-REIT-owned properties that our algorithm identifies.

We find that SF-REITs' property holdings grew from near zero in 2010 to approximately 170,000 units by 2021, representing about 0.4% of the U.S. single-family housing stock. Early in the sample, SF-REITs actively expanded into new geographic areas, but this outward expansion largely plateaued by 2016-2017. Since then, growth has primarily occurred through increased investment within ZIP codes where they already held properties—especially for the two largest firms, INVH and AMH. Notably, SF-REITs initially entered different local markets, with each firm focusing on a distinct set of ZIP codes. Over time, however, their geographic footprints converged. Today, most properties owned by the three largest SF-REITs are located in ZIP codes where all three operate, suggesting that intra-industry competition may constrain the market power of any single SF-REIT.

We also explore the characteristics of the locations that SF-REITs choose to locate and expand their property holdings. We document that SF-REITs' holdings form a "donut" around the central business district without extending far into the suburbs in most of

[5]For evidence on the consumption value of homeownership, see for example, Engelhardt et al. (2010), Hausman et al. (2022), and Sodini et al. (2023).

the metropolitan statistical areas (MSAs). Within MSAs, SF-REITs are typically located in areas where the housing supply is more elastic, consistent with their target locations having few barriers to entry. Moreover, SF-REITs have greater ownership in areas with younger populations, populations that have less income, and a larger minority population. These demographic groups tend to be on the lower rungs of the housing ladder and potentially face greater barriers to homeownership. This finding suggests that SF-REITs are meeting the demand of non-homeowners who might prefer standalone homes as opposed to multi-family dwellings.

Next, we study the relationship between SF-REIT property growth and ZIP code-level housing market outcomes. To estimate the relationship, we augment the long-differences regression approach employed by Acemoglu and Restrepo (2020), which the literature often uses to estimate the effects of gradual processes. The independent variable of interest is the ZIP-code level change in the SF-REIT share of the housing stock between 2012 and 2021. Owing to the ZIP-code level granularity, the regressions include MSA fixed effects. As such, the regressions are identified from spatial differences between neighborhoods with SF-REIT properties benchmarked against neighborhoods without them but are part of the same MSA. Therefore, the regressions confidently rule out confounding shocks that affect the economic region (see e.g., Brown et al., 2017). The regressions also control for ZIP code-level characteristics to account for within-MSA differences in economic trajectories during the period.

Moreover, we develop an empirical approach that further disentangles the empirical estimates of SF-REITs' effects on local market outcomes from their selection of specific ZIP codes within an MSA. Intuitively, the effect on local housing markets should be greater when SF-REITs hold a larger share of the housing stock. On the other hand, estimates derived from the presence of any SF-REIT properties, independent of the magnitude, likely capture the average differences in the ZIP codes where SF-REITs chose to operate. Thus, our modified regression framework includes separate coefficients, a dummy variable for a positive SF-REIT share, and an interaction between the dummy variable and the growth in SF-REIT share. The effects of SF-REITs are more likely driven by selection effects if the estimates load on the dummy coefficient rather than the interaction term (see the graphical example in Figure 6).

Using these empirical designs, we assess claims about SF-REITs' role in reducing housing accessibility in local markets. We start with housing supply, which we measure as the stock of single-family residences in a ZIP code. We find that a one standard deviation increase in SF-REIT property holdings is associated with approximately a 0.6 to 0.7 percentage point larger increase in the stock of single-family residences in a ZIP

code. In addition to boosting the overall housing stock, SF-REIT growth is associated with an increase in the number of single-family residences owned by individuals. However, this result is primarily through a selection channel, suggesting that SF-REITs growth does not supplant individual ownership. Overall, these results show that SF-REIT penetration in local housing markets does not negatively reduce supply, contrary to claims about SF-REITs crowding out individual homeowners.

Next, we find mixed evidence of SF-REITs effect on housing affordability through a pricing mechanism. Specifically, we find a positive relationship between SF-REIT property holdings and home price growth. However, the magnitude is small: a one standard deviation increase in the share of SF-REITs translates into 0.14% higher annual price growth, over a sample period in which U.S. house prices grew by 6.7% on average per year. Moreover, there is no evidence that the price increase has negative effects on local home-buyers through channels of increased buying competition or reductions in market liquidity. To the former, the SF-REIT share is negatively related to the sales-to-list price ratio, suggesting no evidence of increased home buying competition driving price markups. We also find no change in the number of days on the market for new listings. As such, the positive relation between SF-REITs and home prices is most consistent with SF-REITs having complementary effects on neighborhood development (see e.g., Gurun et al. 2023). Since SF-REITs purchased properties in areas where buyers are more likely to have been constrained, our evidence segues with findings that SF-REITs helped with neighborhood recoveries post-crisis (e.g., Molloy and Zarutskie 2013; Mills et al. 2019; and Lambie-Hanson et al. 2022, among others).

Lastly, we find no evidence that SF-REITs reduce house purchase financing accessibility for local buyers. Specifically, ZIP codes with SF-REIT property holdings have not experienced differential changes in borrower FICO scores or loan-to-value ratios. These findings suggests that SF-REITs ownership has had minimal effect on the composition of credit characteristics of home buyers. Moreover, loan approval rates have not changed in ZIP codes with a larger SF-REIT share. We would have expected an increase in mortgage denials if households were straining to purchase properties in locations with a larger precess of SF-REITs.

Since our combined findings suggest that the effects of SF-REITs on local housing markets are either economically modest or statistically indistinct from zero, we conduct a thorough examination of the robustness of these null results. In settings where effect sizes are small, concerns about model specification, measurement error, and omitted variable bias become particularly salient. To address these issues, we implement a Specification Curve Analysis (SCA) to test the stability of our estimates across a wide range of defen-

sible modeling choices (Simonsohn et al., 2020). We also apply bounding techniques to assess the potential role of unobservables (Oster, 2019) and conduct simulation-based analyses to evaluate how measurement error in our SF-REIT ownership variable might attenuate our results. Taken together, these exercises demonstrate that the limited effects we document are not artifacts of estimation choices or data limitations, but instead reflect a consistent pattern: SF-REITs have had, at most, modest effects on housing supply, prices, and accessibility for individual buyers.

1.1 Related Literature

Our paper contributes to the broad literature exploring how institutional investors affect households and markets. Recent research studies the effects of institutional investors on employment, healthcare, and consumption, often in adverse ways.[6] Our interest lies in the single-family housing sector, which until recently has seen little institutional activity. Most recent studies on residential real estate investments by institutions have focused on the role these investors played in stabilizing local housing prices and regional markets following the Great Recession.[7] An earlier literature investigated short- to medium-term housing speculation, often by individual investors, which played a significant role in fueling the housing market surge that led up to the 2008 Great Recession.[8] There is also considerable research studying real estate investments, particularly the returns to housing and individual real estate assets, and to commercial REITs.[9]

Our paper shifts the focus to recent policy debates on housing access and individual ownership affordability by examining the role of long-term investors in recent periods marked by significant home price increases. As a result, policymaking conclusions drawn from our research diverge from earlier studies focused on the housing recovery, especially as housing affordability now holds a central place in policy discussions. Recent legislative proposals have targeted investors in single-family homes, with the goal of reducing their footprint, under the assumption that this would ease access to ownership for individuals. For example, the *Stop Predatory Investing Act (S.2224)*, suggests eliminating tax breaks for interest payments and depreciation for any taxpayer owning fifty or more single-family properties.

[6] See, e.g., Flynn and Ghent, 2022; Chodorow-Reich et al., 2021; Gupta et al., 2024; Fracassi et al., 2022.

[7] See e.g., Immergluck and Law, 2014; Favara and Imbs, 2015; Raymond et al., 2016; Gete and Reher, 2018; Mills et al., 2019; Smith and Liu, 2020; Lambie-Hanson et al., 2022; Garriga et al., 2023; Ganduri et al., 2023.

[8] See e.g., Chinco and Mayer, 2016; Bayer et al., 2021; Nathanson and Zwick, 2018; Gao et al., 2020; Bayer et al., 2020.

[9] See e.g., Jorda et al., 2019; Chambers et al., 2021; Sagi, 2021; Giacoletti, 2021; Demers and Eisfeldt, 2022 and Cotter et al., 2018; Ling et al., 2019, 2018; Van Nieuwerburgh, 2019; Ghent, 2021.

A few recent papers examine how institutional landlords influence housing markets, particularly through effects on rents and neighborhood quality. Yet there is little consensus. For example, Gurun et al. (2023) exploits institutional mergers to identify local changes in the market presence of institutional landlords. They find that rents increase, but neighborhood quality also improves. In contrast, Billings and Soliman (2024) uses a ring difference-in-differences design in North Carolina and finds that nearby home prices decline and neighborhood conditions worsen (higher crime rates and worse maintenance). Francke et al. (2024) study a regulatory ban on investor purchases in the Netherlands and find no price effects but evidence of compositional shifts toward owner-occupiers, consistent with gentrification.

Our contribution relative to these studies is twofold. First, we focus directly on homeownership access—the subject of recent policy debates—rather than rents or neighborhood quality. Second, we use a national dataset that tracks the expansion of SF-REITs, long-term institutional landlords that, unlike other investors, do not switch between buy-and-hold and speculative strategies. This focus enables us to isolate the long-run effects of institutional presence from the short-run yield chasing activities of other investor types.

By shifting the focus toward homeownership access (house prices, supply, and credit), our paper complements contemporaneous studies on housing market competition following the introduction of institutional landlords. Given the novelty of this area, these concurrent works all address these questions with different samples and with different empirical designs, helping produce a body of evidence that will no doubt be useful to the literature and policy. In this vein, Gorback et al. (2025) find increased house prices, reduced homeownership, but only negligible effects on rents. They, however, use an instrumental variable strategy and a broader measure of institutional investors. Coven (2023) adopts a quantitative general equilibrium model and concludes that institutional rental investors increase supply and reduce rents but modestly depress homeownership, with small average price increases that are attenuated by the supply increase.

Our paper finds that larger increases in SF-REITs in a local market are associated with both greater price and supply growth. Yet, interestingly, the number of units owned by individuals also grows by nearly as much. Crucially, we show that the magnitude of the effects on prices is small, and that there is no evidence of an increase in the credit burden faced by new homeowners, since both mortgage approval rates, as well as loan-to-value ratios and FICOs of originated loans, are unaffected. Though our long-difference empirical strategy is perhaps the most straightforward, we investigate the possibility that estimates might be attenuated, either by omitted variable biases or measurement error. We use state-of-the-art techniques such as SCA, Oster bounds, and a simulation-based analysis of

measurement error to bound biases. These methods allow us to argue credibly that even with possible attenuation, the effects of SF-REITs on access to homeownership remain modest.

2 Institutional Details and Data on SF-REITs

2.1 Institutional Details on SF-REITs

A real estate investment trust (REIT) is a corporation that acquires, manages, and develops real estate properties, or owns related mortgage investments. REITs often function as large-scale landlords of commercial and residential properties, and their main source of revenue comes from rent from tenants. REITs attract a wide range of investors including individual households and institutional investors such as pension funds, endowments, foundations, insurance companies, and banks. Many REITs are public companies listed on stock exchanges. As a result, REITs usually have greater liquidity than direct real estate investors and therefore have greater ability to scale operations including through purchases of existing property.

Moreover, REITs offer tax advantages that set them apart from typical corporations. First, they avoid the double taxation of dividends. Unlike most corporations, REITs do not pay corporate taxes on their earnings. Instead, they distribute their untaxed income to shareholders who are then taxed at the individual level. Another relatively new tax advantage of REITs is their ability to pass through deductions under the Tax Cuts and Jobs Act of 2017. REIT dividends may qualify for a deduction of up to 20% of pass-through income.

To qualify for these tax advantages, REITs must adhere to requirements set forth by the Securities and Exchange Commission (SEC).[10] First, REITs are not allowed to generate much revenue through property re-sales (i.e., property flipping). This "investment term" rule ensures that REITs are long-term real estate investors rather than short-term speculators (see Schneider et al., 2022). The SEC enforces this rule by requiring that REIT properties produce rental income and remain in the REIT for at least two years, and that the REIT does not sell more than seven properties in a year ("safe harbour rule"). REITs that fail these tests must pay corporate taxes and penalties of up to 100% of capital gains on properties they resell.

Second, the SEC requires REITs to invest at least 75 percent of their total assets in real estate. Also, REITs must derive at least 75 percent of their gross income from real

[10] See the *2011 SEC Bulletin* for an overview.

estate–related activities such as rental income and proceeds from property sales. Third, the SEC mandates that REITs distribute at least 90 percent of their taxable income to shareholders annually via dividends.

To meet these requirements, and thus maintain their advantageous tax status, REITs typically hold onto their real estate properties for long horizons. They focus on long-term asset management and rental income generation rather than opportunistic property flips. Nonetheless, long-term price appreciation is also an important component of the value of REITs' investment portfolios.

Our analysis focuses on single-family REITs (SF-REITs), which like other REITs, collect rent from tenants and distribute rental income to their investors. The key distinction from other REITs is that SF-REITs are in essence large-scale landlords for single-family homes, as their name suggests. SF-REITs are perhaps uniquely interesting to study because they operate in a market in which they directly compete with household property buyers, both those that own and occupy their residences and those that generate rental income from their property. Single family housing has historically been the domain of the individual household whereas multifamily housing, such as apartment complexes, are typically financed and often owned and rented out by an enterprise, such as medium scale landlords or REITs. However, SF-REITs have been the dominant pathway for corporate entities to enter single family housing markets as we describe in the following sections.

2.2 Data Construction

We identify SF-REITs' ownership of single-family homes using CoreLogic Tax assessment data. These data, collected by CoreLogic, are compiled from county public records. The data include the location of the assessed property, the owner's name and owner mailing address, and the assessed value of the property. We restrict our analysis to the sample of single-family homes.

Because developing our data set of SF-REITs ownership is resource intensive, we focus on geographic locations specifically mentioned in the SF-REITs' 10-K filings. Thus, our data collection comprises 16 U.S. states: Arizona, California, Colorado, Florida, Georgia, Illinois, Indiana, Minnesota, Nevada, North Carolina, Ohio, South Carolina, Tennessee, Texas, Utah, and Washington.

We focus on identifying SF-REITs' ownership for the largest SF-REITs.[11] The largest SF-REITs are Invitation Homes, American Homes 4 Rent, and Tricon. Our sample also includes smaller SF-REITs, namely Starwood, Colony American, and Altisource/Yard.

[11] Our approach follows previous work in the literature including, among others, Lambie-Hanson et al. (2018) and Mills et al. (2019).

To identify ownership by specific SF-REITs, we start by conducting a keyword search for the owners' names. For example, to identify single-family homes owned by Invitation Homes, we use the keywords "INVITATION" and "IH BORROWER." Highlighting the challenges of data construction, this simple keyword search yields few matches. SF-REITs often set up limited liability corporations (LLCs) as subsidiaries that acquire and manage properties under completely different names and do not use their main corporation name as the owner name on a deed.

Next, we improve the match rate by compiling a list of buyers' mailing addresses from the SF-REITs properties we identified in the previous keyword search (see also Ganduri et al., 2023).[12] We then use this list of buyers' mailing addresses to identify SF-REITs ownership for the full sample of property tax records in CoreLogic regardless of the name of the property owner. We iterate over this procedure multiple times in order to get a more complete list of SF-REITs owners. The details of these steps are discussed in Appendix A1. In addition to the steps described above, we conduct manual checks to ensure the accuracy of our approach to identifying SF-REITs' property holdings.

We find that our procedures for the data construction do a good job of identifying SFR ownership. For example, Table 1 shows the number of properties owned by INVH and AMH in each state in 2021. The table compares the number of properties identified by our matching procedure and the total given in their company's 10-K filings.[13] The table shows that the geographical distribution of property holdings in our constructed data set mirrors the geographic distribution in 10-K filings. The total number of matched properties is approximately equal to 90% of that reported by Invitation Homes in its 10-K public filings. We assign slightly more properties to AMH than are listed in its 10-K. Combined, these suggest that errors in our procedures for assigning SF-REITs property holdings are random and likely uncorrelated with outcomes of interest in our subsequent statistical analysis.

We use our data to construct, at the ZIP code level, the share of single-family units owned by SF-REITs between 2012 and 2021. As we discuss below, the change in this share is the key independent variable in our empirical tests. Table 2 displays summary statistics of the change in the share of SF-REITs across zip codes, along with summary statistics of outcome variables of interest and controls.

[12]Specifically, we use the buyer's mailing address variable from the CoreLogic data set.

[13]The SF-REITs do not always list the number of properties in a state in their 10-K filings, but our matching approach still locates these properties (see e.g., AMH holdings in Seattle, WA).

3 The Growth of Single-Family REIT Property Holdings

This section describes the growth of SF-REITs' property holdings throughout the U.S. First, we describe the economic conditions that fostered the growth of REIT investment in single-family housing. Then, we catalog the growth of SF-REITs property holdings over time and their geographic footprint. The findings and discussion in this section are potentially crucial to understanding how SF-REITs may affect local housing markets.

3.1 Housing Market Conditions Fostering the Growth of SF-REITs

SF-REITs entered U.S. housing markets in the aftermath of the Great Recession and the housing crisis. The following factors are among the leading contributors to the growth of SF-REITs in the post-crisis period.

First, the demand for rental housing increased after the Great Recession. The crisis resulted in tighter credit standards for many households. After the Great Recession, households had less wealth on average and faced financing constraints that made it more difficult to purchase homes (D'Acunto and Rossi, 2022). Household risk aversion could have also increased after experiencing the housing crisis (see e.g., Goodman and Mayer, 2018; Fritsch and Heimer, 2020). These factors combined to increase demand for rental properties, including single-family homes.

Second, low interest rates and depressed house prices forged a pathway for institutional investment in single-family rental properties. Specifically, residential house prices dropped by approximately 25% from peak to trough, and the market did not show significant signs of recovery until the mid-2010s. The reduction in home prices coincided with a substantial increase in foreclosures (Mian et al., 2015). Moreover, the Federal Reserve lowered the Federal Funds Rate to close to zero for a prolonged period of time. As such, institutional investors, with increased access to capital through low interest rates, saw an opportunity given bargain prices to earn high rental yields and earn long-term capital gains.

Lastly, but not exhaustively, advancements in information technology played a role in the rise of SF-REITs. Such advancements have made it easier for the management of SF-REITs operations to set rental prices and manage payments, as well as schedule and address maintenance.[14] Property management would have been less economical for SF-REITs because single-family homes are diverse and dispersed. Therefore, pricing and

[14]See https://www.npr.org/transcripts/1197961038 for an example of rental pricing algorithms.

operations would have required more localized expertise giving a comparative advantage to local ownership.

3.2 The Growth of SF-REITs Property Holdings

This section first describes the locations that SF-REITs have chosen to operate. Several patterns emerge from observing the geographic property holdings presented in Table 1. First, SF-REITs properties are not uniformly spread around the country. Instead, they are located in a handful of states and metropolitan areas. The decision to cluster in certain locations is likely due to economies of scale (Yu, 2023), or, as we discuss in the following sections, the fact that SF-REITs seek specific locations and demographic groups. Second, the two large SF-REITs own 135,000 properties. As such, SF-REITs property holdings, though significant, still constitute a small share of the total single-family housing stock.

We begin by cataloging the time series of SF-REITs property ownership. Panel (a) of Figure 1 plots the number of properties owned by SF-REITs for each year between 2010 and 2021. The blue solid line shows the total number of properties owned by top 3 SF-REITs—INVH, AMH, and the Canadian owned REIT Tricon.[15] The red dashed line shows the holdings of an extended list of SF-REITs. SF-REITs own almost no properties in 2010. SF-REITs quickly expand in the following years. The top 3 SF-REITs own approximately 125,000 properties and our expanded list owns 150,000 in 2016. SF-REITs' growth slowed substantially since 2016. SF-REITs added just around 30,000 units in total between 2016 and 2021. Panel (b) shows the holdings of SF-REITs as a share of all single-family homes. Though the share grew quickly during the sample period, it leveled off in the latter years at approximately 0.3% of the total housing stock.[16]

Figure 2(a), compares the growth rates of the three largest SF-REITs to both one another and to our expanded set of SF-REITs. AMH and INVH grew the quickest at the beginning of the sample. Tricon only began expanding its portfolio in 2014-2015. Meanwhile, other SF-REITs grew sharply until 2014. After 2014, other SF-REITs reduced their property holdings suggesting an increase in market concentration among the largest SF-REITs.

Figure 2 also presents changes in the spatial distribution of SF-REITs holdings over time. The three largest REITs increase the average number of properties owned in a given ZIP code (panel a). Furthermore, INVH and AMH increase the total number of ZIP codes

[15] In January 2024, Tricon was acquired by Blackstone and taken private. However, for the entire sample period of our study, Tricon was a publicly traded REIT.

[16] Figure A1 in the Appendix presents the analogous figure for the share of SF-REITs units out of all absentee units. Similarly to all housing units, SF-REITs grew significantly as a share of the housing stock before leveling off at approximately 2%.

in which they operate until 2016-2017. They have stopped expanding geographically by the end of the sample. INVH is present in approximately 2,000 ZIP codes in 2021-2022 and AMH is present in 1,500. On the other hand, Tricon began increasing its portfolio later in the sample and is still increasing the number of ZIP codes where it operates.

Finally, we find that SF-REITs have a persistent presence in the ZIP codes where they operate (Figure 2, panel (b)). Starting in 2013, we select all ZIP codes where an SF-REITs has holdings, and calculate the share of ZIP codes in which the same SFRs had holdings three years prior. The shares steadily increase over the sample period, and for INVH and AMH they are above 95% starting in 2019. The share is slightly lower for Tricon but still equal to 80% in the last two years of the sample.

In summary, SF-REITs have steadily increased their presence within and across ZIP codes, especially between 2010 and 2016-2017. The growth of the two largest SF-REITs leveled off in the latter part of the sample. They operate within a stable set of ZIP codes and have focused on increasing their property holdings in the ZIP codes where they already operate. Tricon, which began operations more recently, is still expanding its geographic presence in the later years of the sample.

3.3 SF-REITs Market Concentration and Local Market Characteristics

The previous section shows that SF-REITs have persistent ownership within a ZIP code and they expand mostly within existing ZIP codes rather than to new ZIP codes. We follow this analysis by exploring the extent of competition between SF-REITs in a given neighborhood. Figure A2 shows the extent to which the three major SF-REITs overlap in the same ZIP code. In the early years of the sample, the different SF-REITs operate in distinct and separate locations around the country. Many ZIP codes have properties owned by a single SF-REITs, usually either AMH or Tricon. Following 2018, the majority of properties owned by the three major SF-REITs are in ZIP codes where other SF-REITs—both the three major SF-REITs and smaller SF-REITs—all operate. Overall, SF-REITs started operations in separate locations before converging in the same neighborhoods, suggesting high levels of competition in the sector.

Next, we study where SF-REITs choose to operate to fuel their growth of property ownership. The maps in Figure 3 present the share of SF-REITs properties by ZIP code in a given MSA in 2021.[17] SF-REITs properties tend to concentrate in a "donut" of neighborhoods surrounding the city center. SF-REITs own fewer SF-REITs properties in the inner city and outer suburbs.

[17]The MSAs are Atlanta (GA), Charlotte (NC), Dallas (TX), Houston (TX), Indianapolis (IN), Jacksonville (FL), Miami (FL), Nashville (TN), Phoenix (AZ), Raleigh (NC), and Tampa (FL).

Figure 4, panel (a), shows that the share of single-family residences owned by SF-REITs in 2021 is positively associated with the share of foreclosures in 2010. This finding is consistent with SF-REITs taking advantage of the fire-sale conditions post-crisis to expand in residential housing markets (as described in Section 3). Panel (b) shows that SF-REITs properties are positively associated with local supply elasticity. This suggests that SF-REITs have focused on neighborhoods where they can expand and scale up operations. The result complements our findings that SF-REITs have grown the most by expanding within locations where they already operate. We also find that SF-REITs operate in neighborhoods that experienced more overall population growth and increases in rental prices (panels (c) and (d)). SF-REITs may have anticipated increased demand for their rental properties in these neighborhoods.

To gain insight into the consumer groups that demand single-family rentals operated by SF-REITs, we explore the demographic characteristics of neighborhoods where SF-REITs own a significant fraction of the housing stock. Figure 5 shows a negative association with income per capita (panel a), and a positive association with the share of young people and minorities (panels (b) and (c)) both in 2013 and the latter years of our sample (2021). The relation with the share of college graduates is less clear, but the largest shares of SF-REITs properties are in ZIP codes with a low share of college graduates (panel (d)).

Overall, the evidence points to the fact that SF-REITs have focused on less affluent mid-city markets. These neighborhoods have high supply elasticity within their metropolitan area and were more strongly affected by the housing bust. These markets are populated by lower income, younger, and more racially diverse households—households that are on the lower rungs of the housing ladder. Moreover, these neighborhoods experienced more population growth and larger increases in rental prices.

4 SF-REITs and Market Outcomes

The previous section shows that SF-REITs have emerged as a significant entity in a particular segment of local housing markets. Since SF-REITs have concentrated in certain neighborhoods within certain MSAs, they have plausibly affected local housing markets. The following section studies how SF-REITs' property growth affects housing market conditions in these neighborhoods.

4.1 Estimation Approach

To estimate the relationship between SF-REITs property growth and local market outcomes, we adopt a long-differences regression empirical strategy. The literature often employs

long-differences to estimate the effects of gradual processes such as long-run technological shocks (see e.g., Acemoglu and Restrepo, 2020). We augment the estimation procedure by incorporating spatial differences to mitigate the effects of contemporaneous economic shocks on the regression estimates (see e.g., Brown et al., 2017). Intuitively, the spatial differences help the regression model isolate effects in specific locations by benchmarking changes in neighborhoods that experienced SF-REITs growth against other neighborhoods that did not. This helps mitigate the confounding effects of economic conditions across an integrated geographic region.

Specifically, our regressions estimate the following equation:

$$\Delta y_{z,12:21} = \beta \Delta SFR_{z,12:21} + BX_z + \alpha_{Metro} + e_z, \tag{1}$$

where $\Delta y_{z,12:21}$ is the 2012 to 2021 change in an outcome of interest in ZIP code z. The main independent variable is the change in the share of single-family residences owned by SF-REITs ($\Delta SFR_{z,2012:2021}$). MSA fixed effects are denoted α_{Metro}. Moreover, because the standard deviation of $\Delta SFR_{z,12:21}$ is 0.40, the coefficient estimate of β is equivalent to approximately a 2.5 standard deviation growth in SFR share.

Though the regression model suppresses the effects of economic trends at an MSA level, we are cautious to interpret causality to the estimates of β. Differences in economic trajectories across ZIP codes *within* an MSA can also drive differences in estimates. To the extent that we can rule out such confounds, equation (1) also includes a vector of ZIP code level controls (X_z) that includes personal income and the ages, gender, and racial composition of the population.

Moreover, SF-REITs' decision to operate in certain ZIP codes within an MSA could explain their relation to market outcomes (i.e., through a selection channel). As such, within-MSA heterogeneity and the possibility that different neighborhoods have had different trajectories since 2010 can affect estimates of β. For instance, SF-REITs might have targeted neighborhoods that they expected to grow rather than SF-REITs being the cause of such growth.

To separate the treatment effects of SF-REITs from average differences in their selection of neighborhoods, we posit that the magnitude of SF-REITs' growth in a neighborhood should relate to whether their presence has measurable effects on neighborhood outcomes (similar in spirit to the "tipping point" mechanism in housing choice described in papers such as Card et al., 2008). For instance, SF-REITs likely shape a neighborhood if they own a substantial share of the housing stock. Yet an SF-REITs is likely to have merely explored

operations in a given neighborhood if they purchase at least one property but few more. Such limited operations are unlikely to affect housing markets.

Therefore, we design an alternative regression specification to make progress in isolating the effects of SF-REITs' neighborhood selection. Specifically, we also estimate:

$$\begin{aligned}\Delta y_{z,12:21} = \gamma_0 I_{\Delta SFR_{z,12:21}>0} + \gamma_1 \left(\Delta SFR_{z,12:21} \times I_{\Delta SFR_{z,12:21}>0}\right) \\ + GX_z + \delta_{Metro} + u_z,\end{aligned} \tag{2}$$

where $I_{\Delta SFR_{z,12:21}>0}$ is an indicator variable that equals one if the share of SF-REITs properties in the ZIP code increases between 2012 and 2021. The coefficient γ_0 captures the association between *any* increase in SF-REITs ownership and ZIP code outcomes. The coefficient γ_1 captures the effects associated with incremental increases in the share of the housing stock owned by SF-REITs. Essentially, equation (2) is similar to a regression discontinuity at zero, which is a credible empirical strategy employed across literatures (e.g., Ben-David and Hirshleifer, 2012). When interpreting the regression results, coefficient magnitudes that increase with increases in SF-REITs ownership are more likely to be driven by SF-REITs penetration on the local market (measured by a positive coefficient on γ_1) whereas estimates due to the simple presence of SF-REITs are more likely to be driven by selection of SF-REITs into a given neighborhood (captured by γ_0). Figure 6 provides a graphical depiction of the two cases: γ_0 is negligible, and γ_1 is positive, and the opposite, γ_0 is positive and γ_1 is negligible.

Importantly, our estimates capture the aggregate effects of SF-REITs penetration on a given ZIP code. An alternative empirical approach is to study the effects of spillovers from one individual SF-REITs property to its immediate surroundings (e.g., Billings and Soliman, 2023). Testing for effects property-by-property can offer stronger claims to identification because of precision; however, coefficient estimates might be subject to the "reflection problem" in which it becomes challenging to rule out reverse causality (Manski, 1993). Since different levels of aggregation have benefits and drawbacks, we feel that our choice of using ZIP code level observations is supported empirically by the local clustering of SF-REITs properties (see Figure 2) and the approach is well-suited to estimate aggregate effects across integrated housing markets.

Another advantage of our ZIP code-level analysis is that it allows us to incorporate granular, neighborhood-specific measures of housing supply elasticity into our identification strategy. In particular, we augment equation (1) with an interaction for new housing supply elasticity using the sub-MSA estimates from Baum-Snow and Han (2024). The effect of SF-REITs on prices (and other outcomes) would be larger in relatively more

inelastic neighborhoods if they have a causal impact on the market. On the other hand, the correlation between SF-REITs and long-run outcomes could be due to neighborhood selection if effects do not depend on the elasticity of supply.

Beyond our preferred empirical specifications, Section 5 explores the robustness of estimates of equation (1). Of note, we explore the role of outliers in SF-REITs penetration across ZIP codes on the estimated effects. Specifically, the distribution of $\Delta SFR_{z,12:21}$ is highly skewed, which might allow outlier ZIP codes to drive average effects. The mean of $\Delta SFR_{z,12:21}$ is 0.11% and its standard deviation is 0.40%. The median value is 0, the 75th percentile is 0.02% and the 95th percentile is 0.74%. We estimate equation (1) both in the full sample and in a subsample restricted to values of $\Delta SFR_{z,12:21}$ smaller than or equal to the 95th percentile (0.74%). Section 5 also explores the dependence of any relationship on neighborhood characteristics. Specifically, we incorporate ZIP code level personal incomes and foreclosure rates in 2012, both of which are associated with SF-REITs' market entry at the start of our sample.

4.2 SF-REITs' Effects on Housing Supply

We start by analyzing the relationship between the growth of SF-REITs and the supply of single-family residences. The potential for SF-REITs to impact housing supply is unclear. On one hand, SF-REITs' growth could stimulate neighborhood investment by developers and individual homeowners, thereby increasing housing production. On the other hand, the presence of SF-REITs might have no effect or even reduce the supply of new homes for owner-occupiers. Understanding this dynamic is essential to assess whether SF-REITs complement or crowd out potential homeowners in local markets.

Table 3, Panel A, presents the results of our long-differences regression that estimates the relationship between changes in SF-REITs property holdings and housing supply growth. The baseline specification, shown in column (1), includes no additional controls or fixed effects. We estimate a coefficient of 2.17, suggesting that a one standard deviation increase in SF-REITs share growth (0.4%) is associated with a 0.86% larger annual growth in housing supply. Column (2) introduces controls for ZIP code characteristics and metropolitan area fixed effects. The inclusion of these controls reduces the estimated coefficient to 1.32, indicating that part of the observed relationship is driven by underlying differences across ZIP codes.

To isolate the effects of SF-REITs from their selection into specific neighborhoods, we employ a modified regression specification as outlined in equation (2). This approach includes both a dummy variable indicating any positive change in SF-REITs share and

an interaction term capturing the magnitude of SF-REITs growth. The results, presented in column (3), reveal a significant positive coefficient for the dummy variable, and an estimate of the interaction term that is equal to 0.66, half the magnitude of the coefficient in column (2), and borderline statistically significant. This result suggests that the positive relationship between SF-REITs growth and housing supply is likely driven by SF-REITs' neighborhood selection rather than a causal effect on supply growth.

Finally, column (4) interacts SF-REIT growth with housing supply elasticity. The interaction coefficient is negative but not statistically different from zero. The absence of a positive interaction effect is suggestive of a selection channel rather than a positive effect on housing supply. Overall, the growth of SF-REITs relates positively to housing supply growth, but the evidence for a causal effect is not strong.

Panel B examines whether SF-REITs have had effects on housing supply for individual owners. The dependent variable is the growth rate of the number of units owned by individuals. The coefficient estimates are similar to those in panel A, suggesting that a higher share of SF-REITs in the ZIP code is associated with an increase in units owned by individuals of similar magnitude as the overall increase in housing units. However, it is again difficult to rule out neighborhood selection from a causal channel. In column (3), the estimate of the interaction term in the non-linear specification is statistically insignificant while the coefficient on the SF-REITs dummy variable is positive. In column (4), the interaction term on supply elasticity is negative and not statistically significant. Combined, these results suggest that SF-REITs have not constrained the growth of single-family ownership by individuals. Instead, without claiming a causal relationship, they plausibly complement individual ownership in a neighborhood.

4.3 SF-REITs' Effect on House Prices and Market Liquidity

Next, we examine the effects of SF-REITs growth on home prices and housing market liquidity. Starting with house price growth, the dependent variable in Panel A of Table 4 is the annualized percentage change in the average house price in ZIP codes from 2012 to 2021. We generally find positive effects on house prices, but a few features of the regressions are notable. First, the coefficient in regressions with MSA fixed effects is almost four times smaller than without them (column 2 versus column 1), consistent with SF-REITs selecting on economic regions that experienced more price growth ex-post. Second, the effects in column (3) are driven by the linear term in the interactive regression, while the coefficient on the dummy for any SF-REITs is also positive and statistically significant, consistent with both selection and causal effects on prices. However, in column (4), we fail

to provide additional support for causality; the interaction with supply elasticity is not statistically different from zero.

Nonetheless, the economic magnitude of the effects on prices is relatively small. Once MSA fixed effects are included, a one standard deviation increase in SF-REITs share corresponds to a 0.14% higher annualized price growth from 2012 to 2021 (column 2). The median house price growth rate per year during the sample period is 6.7%, suggesting that the house price growth attributable to SF-REIT concentration is equivalent to approximately 2% of the factors driving overall house price growth nationally.

To further explore whether the introduction of SF-REIT properties increases price pressure, we examine the sale-to-list price ratio. Intuitively, sellers should command a higher sales price relative to their listing price if SF-REITs exert price pressure. Conversely, SF-REITs might lower prices if sellers are willing to accept discounts for cash purchases (Reher and Valkanov, 2024; Han and Hong, 2024). The gap between listing prices and final sales prices serves as a proxy for the bargaining power of sellers versus buyers.

Panel B of Table 4 sets the dependent variable as the change in the average sale-to-list price (in percentage) between 2012 and 2021. Notably, we find that a one standard deviation increase in SF-REITs share reduces the sale-to-list ratio by approximately 0.20% (column 2). The linear term is responsible for the negative relationship (column 3), but the relationship does not depend on supply elasticity (column 4). These findings suggest that SF-REITs may have reduced seller bargaining borrower, which is consistent with the increase in housing supply we document in Table 3.

Lastly, we assess the impact of SF-REITs on market liquidity by examining time on the market. Because regulations constrain SF-REITs from reselling properties, an increase in SF-REITs property holdings might reduce liquidity for individual home-buyers. Panel C of Table 4 uses days on market as the dependent variable. We find no significant effects of SF-REITs on days on market. The only notable findings are that SF-REITs select into ZIP codes where single-family properties take longer to sell.

4.4 SF-REITs' Effects on Home-Purchase Financing Accessibility

In this section, we examine whether the expansion of SF-REITs affects local housing accessibility through effects on mortgage financing. If SF-REIT growth intensifies competition for single-family homes and crowds out individual buyers, we would expect to see a shift in the credit characteristics of successful borrowers. Specifically, individual buyers may need stronger credit profiles to compete, and may take on more leverage to afford homes

in these areas. As a result, mortgage denial rates could rise due to both tighter borrower requirements and increased demand for credit.

To assess these potential effects, we analyze the relationship between growth in SF-REIT property ownership and mortgage market outcomes at the ZIP code level. We focus on mortgage approval ratios (the share of approved applications among total applications) as well as the average loan-to-value (LTV) ratios and borrower FICO scores for originated loans.

Panel A of Table 5 presents results for approval rates on new home purchase loans. Across specifications, we find no statistically significant relationship between SF-REIT growth and approval rates. As a robustness check, we repeat the analysis for mortgage refinancing applications (Table A1 in the Appendix), which are less likely to be influenced by direct competition for home purchases. Again, we find no significant effects, suggesting that broader credit market conditions are unlikely to be driving our results.

Panels B and C of Table 5 turn to the composition of approved loans, examining LTV ratios and FICO scores. We find no meaningful changes associated with SF-REIT growth. In refinancing markets (Appendix Table A1, Panels B and C), we observe slight declines in both LTV ratios and FICO scores. LTV ratios decrease by 0.6% and FICO scores decline by 1-point for every one standard deviation increase in SF-REIT share, effects that are economically small.

Taken together, these findings indicate that SF-REIT expansion has not materially altered access to mortgage credit or shifted the composition of borrowers in a meaningful way. While institutional investors may raise concerns about crowding out, we find little evidence of changes in mortgage approval patterns, leverage, or borrower credit quality in areas with higher SF-REIT growth.

5 Robustness of Measurement and Estimation

The core empirical strategy in Section 4 relies on spatial long-difference regressions that relate changes in local SF-REIT penetration to changes in housing market outcomes. The spatial-difference empirical design and the inclusion of relevant control variables mitigate further variation in local economic shocks. We find that SF-REITs are associated with increased housing supply, modest increases in house prices, but no effect on housing accessibility for individual buyers, measured by mortgage approval rates and creditworthiness.

Because the estimates point toward either economically small but statistically significant results, or no effect at all, we explore the precision of our estimates by identifying potential sources of bias in the estimation of equation (1). Specifically, there are three main

concerns: researcher specification choices, omitted variable bias, and measurement error in identifying SF-REITs holdings. This section evaluates the sensitivity of the estimates to each of these vulnerabilities.

5.1 Model Specification Choices

The first threat to inference we consider is sensitivity to researchers' degrees of freedom—namely, whether our main results are robust to reasonable changes in modeling decisions, control variables, and sample restrictions. To assess this threat, we implement a Specification Curve Analysis (SCA) following Simonsohn et al. (2020). This approach systematically explores how estimated effects vary across a grid of plausible empirical specifications. Rather than privileging any single preferred model (as in equation 1), SCA characterizes a robust distribution of effect estimates and identifies conditions under which results are sensitive or robust.

Our SCA varies four key dimensions of the regression setup: (i) the inclusion of MSA-level fixed effects to account for broader regional trends, (ii) the loading on ZIP-code demographic and housing market attributes (e.g., household incomes and supply elasticity), and (iii) the inclusion or exclusion of ZIP codes with the largest share of SFR properties (i.e., filtering for outliers). Fourthly, (iv) the SCA considers alternative definitions of the key independent variable of interest. We estimate all specifications using ΔSFR (the change in the share of REITs holdings), and then replace it with changes in the share of holdings for each of the three largest REITs (Invitation Homes, American Homes 4 Rent, and Tricon), and with the change in the share of units owned by corporate owners that are not REITs.

We generate 100 different specifications by combining these dimensions and estimate each version of the long-differences regression (equation 1) separately for each outcome of interest. We then plot the coefficient on SF-REITs ownership share across the 100 model variants sorted by coefficient size. Each point represents an estimate from a distinct specification and open circles indicate statistical significance at the 5% level.

We highlight the SCA results for housing supply and house price growth because these are key results with statistically significant but economically small effects in the preferred model specification. Starting with housing supply in Figure 7, most estimates are close to the value from our preferred specification (highlighted by the dotted vertical red line) around smaller values. Larger and economically more significant estimates can be obtained only when the top 5% of ZIP codes by SF-REITs presence change are excluded from the data. Mechanically, this data trimming limits the sample to small changes in SF-

REITs share, which implies that the effects of SF-REITs shares on supply are economically small.

Figure A3 displays similar results for the change in the number of units owned by individuals. Again, the estimates are amplified when MSA fixed effects are omitted. Omitting the top 5% of ZIP codes increases the magnitude of the estimates on SF-REITs' growth.

Figure 8 displays results for house price growth. Again, we find that most estimates are similar to the coefficient value obtained from our preferred specification in Table 4. However, some choices drive the coefficients to zero, while others amplify the coefficients. Estimates are substantially larger in magnitude when MSA fixed effects are omitted, which reinforces the notion that SF-REITs selected regions that have experienced substantial house price growth. The effects are statistically insignificant when ΔSFR is replaced with the change in the share of corporate owners that are not REITs. This suggests that including other institutional investor holding in the analysis does not necessarily increase the estimated local house price impact.

The Appendix presents in Figure A4 and Figure A5 the SCA results for the other outcome variables featured in Section 4. Across these outcomes, the estimated effects of SF-REITs ownership share are generally small in magnitude and statistically indistinct from zero. This pattern holds across nearly all specification permutations.

Overall, the specification curve analysis suggests that the estimates discussed in the previous section for the effects on housing supply and prices are robust to a broad range of reasonable specification choices, and change only in response to sample cuts or omissions of crucial controls. Notably, the estimates are insensitive to the entities—all SF-REITs, specific companies, or broader corporate ownership—that we include in the construction of the SF-REITs growth variable.

5.2 Unobservables Bias

The analysis in the previous section shows that our results are robust across specifications that incorporate a basic set of reasonable controls (most importantly, metro-area fixed effects). However, the set of available controls is not exhaustive, and a substantial portion of the variation in the dependent variables remains unexplained. If we examine the results from equation (1), when including the full set of controls (column 2 in Table 3, Table 5, and Table 4), the R-squares range from a maximum of 80% to a minimum of approximately 8.4%.

It is reasonable to conjecture that a significant share of the variation in the dependent variables may be attributed to unobservale characteristics. Then, unobservables bias may impact our estimates of the coefficient β for ΔSFR, and potentially lead to understate the true magnitudes.

We address this possibility by employing a methodology developed by Altonji et al. (2005) and Oster (2019) that is designed to bound unobservable bias. We use estimates based on the complete set of observable controls (*Long-regression*, analogous to column 2 in the tables), and estimates based on the specification that only includes the main variable of interest, ΔSFR (*Short-regression* analogous to column 1 in the tables). Using estimates of the coefficient for ΔSFR and associated R-squares, we extrapolate the coefficient estimate as if it came from a regression specification controlling for the full universe of unobservable controls.[18]

As shown in Table 6, the "Oster approach" suggests that for most dependent variables, accounting for unobserved controls would push the estimated effects even closer to zero. The primary exceptions are mortgage-related outcomes—approval rates, loan-to-value ratios, and FICO scores. However, even in these cases, the implied magnitudes remain economically small.

5.3 Simulation-Based Analysis of Measurement Error

Overall, our estimates suggest that increases in the local share of properties owned by SF-REITs have had only modest effects on housing market outcomes. However, these estimates may be attenuated due to measurement error in our variable for the ZIP code-level growth of SF-REITs ($\Delta SFRs$). Despite our efforts to comprehensively track the portfolios of major REITs, some properties may be misclassified or omitted, leading to imprecision in the spatial distribution of SF-REIT properties.

We conduct a simulation exercise to assess whether measurement error could account for our findings of modest effects. Overall, this exercise shows that it is generally difficult to reconcile substantial attenuation in the estimates of $\hat{\beta}$ with the observed data, unless one

[18]The extrapolation requires two assumptions: (1) the maximum achievable regression R-square, even when all controls are included, and (2) the relationship between the observable and the omitted control variables for a given increase in R-square. Oster (2019) shows that for a coefficient β of interest, given estimates β_L and β_S in the long- and short-regression, and the corresponding R-squares R_L and R_S, the bound is:

$$\beta^* \approx \beta_L + d(\beta_L - \beta_S)\frac{R_{max} - R_L}{R_L - R_S}$$

where β^* is the bound for the coefficient after accounting for the effects of unobservables, R_{max} is the maximum attainable R-square, and d is the sensitivity of the coefficient to the increase in R-square, due to the inclusion of unobservables. In our tests, we set $d = 1$.

assumes that the latent "true" distribution of SF-REITs holdings is much less concentrated than what we observe in the data.

For the simulation exercise, we assume that:

$$\begin{aligned} y_{z,12:21} &= \beta \Delta SFR_{z,12:21} + BX_z + \alpha_{Metro} + \sigma_e e_z, \\ y_{z,12:21} &= \tilde{\beta} \widetilde{\Delta SFR}_{z,12:21} + \tilde{B} X_z + \tilde{\alpha}_{Metro} + \tilde{\sigma}_e \tilde{e}_z, \\ \Delta SFR_{z,12:21} &= \widetilde{\Delta SFR}_{z,12:21} + \sigma_u u_z, \end{aligned}$$

where the first regression equation corresponds to equation (1), u_z is the measurement error and $\widetilde{\Delta SFR}_{z,12:21}$ is the latent true increase in the share of SF-REITs homes at the ZIP code-level. The measurement error has standard deviation σ_u and correlation ρ with $\widetilde{\Delta SFR}_{z,12:21}$. Due to the presence of measurement error, the estimator of β ($\hat{\beta}$) does not converge to $\tilde{\beta}$.

We run simulations in which we set σ_u, ρ, and $\tilde{\beta}$, draw realizations of u_z and $\tilde{\sigma}_e$, and estimate equation (1) using the simulated data. The mean estimate of the coefficient β across draws corresponds to the empirical (attenuated) estimate, given the calibrated values of the parameters governing measurement error and the underlying unbiased value of the coefficient of interest. We provide a detailed description of the calibration and of the simulation algorithm in Appendix Section A2.

First, before turning to the simulation results, we show that conceptually a large measurement error implies a much more uniform distribution of the SF-REITs growth across different ZIP codes in the country over the sample period, which is inconsistent with our findings in Section 3. In other words, it is important to recognize that choosing large values of σ_u implies that a large portion of the variation observed in $\Delta SFR_{z,12:21}$ must be attributed to measurement error. Consequently, the true latent $\widetilde{\Delta SFR}_{z,12:21}$ must follow a substantially different distribution.

Figure 9 illustrates this point by plotting the Gini coefficient of the latent change in the growth rate of SF-REITs ($\widetilde{\Delta SFR}$) across different values of the ratio of measurement error variance (σ_u^2) over the observed variance of $\Delta SFR_{z,12:21}$. The Gini coefficient measures the dispersion of a variable across observations within a given population, ranging from 0 (perfect uniformity) to 1 (maximum concentration).[19]

[19]The Gini coefficient is not necessarily bounded between 0 and 1 when the variable of interest includes negative values. To address this, we compute the Gini coefficient as half the mean absolute difference across observations, defined as follows:

$$G = \frac{\sum_{i=1:n} \sum_{j=1:n} |x_i - x_j|}{2n \sum_{i=1:n} x_i},$$

When $\sigma_u^2 = 0$, there is no measurement error, and Figure 9 displays the Gini coefficient calculated from the observed data. This value, slightly above 0.8, reflects a high degree of concentration, driven by the skewed distribution of ΔSFR. The solid line in the figure shows how the Gini coefficient declines as σ_u^2 increases, under the assumption that measurement error and the latent value of the change in SF-REITs share are uncorrelated ($\rho = 0$). As measurement error rises, the Gini coefficient falls sharply, dropping to 0.6 when σ_u^2 equals 50% of the variance of the observed change, and to 0.4 when it reaches 80

In this case, substantial measurement error would imply that the distribution of the latent true change in SF-REITs share is much closer to uniform across ZIP codes. This is implausible, as the evidence presented in Section 3 consistently indicates that SF-REITs concentrate their investments in micro-locations with specific characteristics.

The reduction in dispersion is less severe when the measurement error is negatively correlated with the latent change in SF-REITs share. Intuitively, if errors are smaller in ZIP codes that experience large increases in ΔSFR, the upper tail of the distribution, and thus its overall dispersion, is partly preserved. The dotted line in Figure 9 illustrates this: with $\rho = -0.5$, setting σ_u^2 to 50% of the variance of $\Delta SFRs$ produces a Gini coefficient of 0.78, while increasing σ_u^2 to 80% lowers it to 0.70. Although dispersion still declines, the contraction is much less dramatic than in the uncorrelated case ($\rho = 0$).

We then return to the simulation exercise and, for different combinations of σ_u and ρ, identify the value of the true (unbiased) coefficient $\tilde{\beta}$ that yields an attenuated estimate equal to the empirical $\hat{\beta}$ observed in the data (see Appendix A2).

Figure 10 presents the simulation results for housing supply and house price growth. Under the assumption that $\rho = 0$, we find that generating latent coefficients $\tilde{\beta}$ substantially larger than the empirical estimates $\hat{\beta}$ requires setting σ_u^2 to at least 50% of the variance of ΔSFR. However, as discussed earlier, such levels of measurement error imply an implausible distribution of the latent variable $\widetilde{\Delta SFR}$.

When the dependent variable is price growth, setting σ_u^2 equal to 50% of the variance of ΔSFR gives a value of $\tilde{\beta}$ close to 1, almost three times higher than $\hat{\beta}$ in the data. However, this also implies that the Gini coefficient of $\widetilde{\Delta SFR}$ would fall to 0.6. Pushing σ_u^2 to 80% of the variance of ΔSFR gives a value of $\tilde{\beta}$ approximately equal to 2.25, but this comes with a Gini coefficient below 0.4.

As shown in Figure 9, assuming negative values of ρ reduces the impact of measurement error on the distribution of $\widetilde{\Delta SFR}$. However, the dotted lines in Figure 10 illustrate that this assumption also reduces the maximum values of $\tilde{\beta}$ that can be reconciled with the observed estimates $\hat{\beta}$, across all levels of σ_u^2. Returning to the price growth example, when

where x_i and x_j are observations, and n is the total number of observations.

$\rho = -0.5$ and σ_u^2 is set to 50% of the variance of ΔSFR, $\tilde{\beta}$ is approximately 0.5. Even at σ_u^2 equal to 80% of the variance, the implied $\tilde{\beta}$ rises to just above 1, which is substantially lower than in the case where $\rho = 0$.

Figure A6, Figure A7, and Figure A8 display results for the other dependent variables analyzed in Section 4. The main insight from these graphs remains the same as in Figure 10. It is difficult to reconcile substantial attenuation in the estimates of $\hat{\beta}$ with the data unless one assumes that the true distribution of SF-REITs holdings across ZIP codes is far more uniform than what is empirically observed.

6 Conclusion

Single-family REITs have grown considerably since the Great Recession and they have garnered significant attention from policy-makers for their potential effects on local housing markets. Though SF-REITs own a small share of the single family housing stock in the U.S., their rapid growth, particularly in certain locations, has raised concern that they affect rates of homeownership and affordability. These concerns arise because SF-REITs often purchase the same properties that might otherwise be sold to individual home buyers.

This paper provides a novel cataloging of the growth of SF-REITs and explores their effects on housing local markets. First, we show that SF-REITs invest in specific neighborhoods within a metropolitan area. They choose ZIP codes located within urban belts between the central business district and the far suburbs, neighborhoods with elastic housing supply, and that have populations that are on the lower rungs of the homeownership ladder and might even face barriers to homeownership (e.g., less income, younger, and more likely to be minorities).

Then, we study the relationship between increased SF-REITs property holdings and local housing market outcomes. Our main results are the following: 1) SF-REITs property holdings are positively correlated with increased local housing stock, with the number of units owned by individuals growing at nearly the same pace. 2) SF-REITs property holdings are positively associated with house price growth but the economic magnitude is small. 3) The growth of SF-REITs has had no effect on home accessibility as measured by the credit characteristics of buyers and mortgage approval rates. Overall, rather than disrupting housing markets, SF-REITs have on average modest effects on local housing markets.

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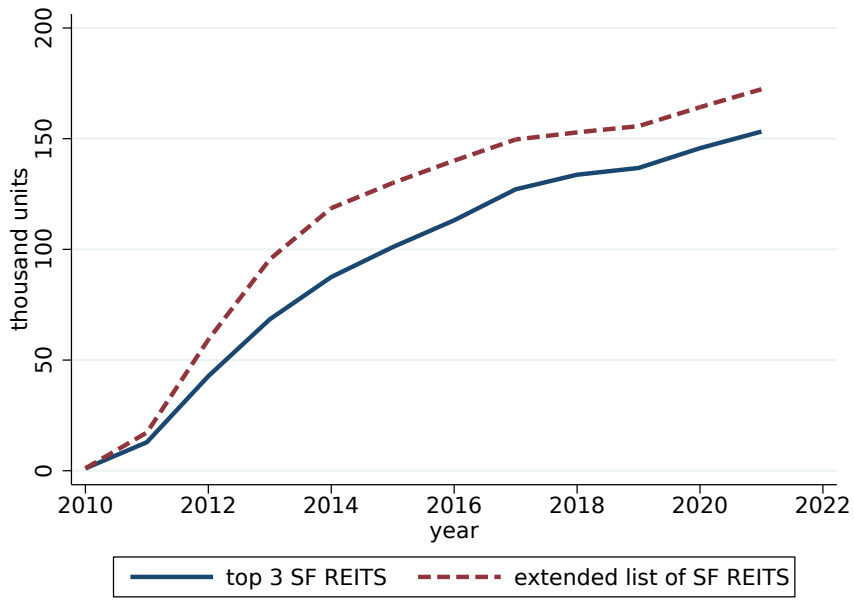
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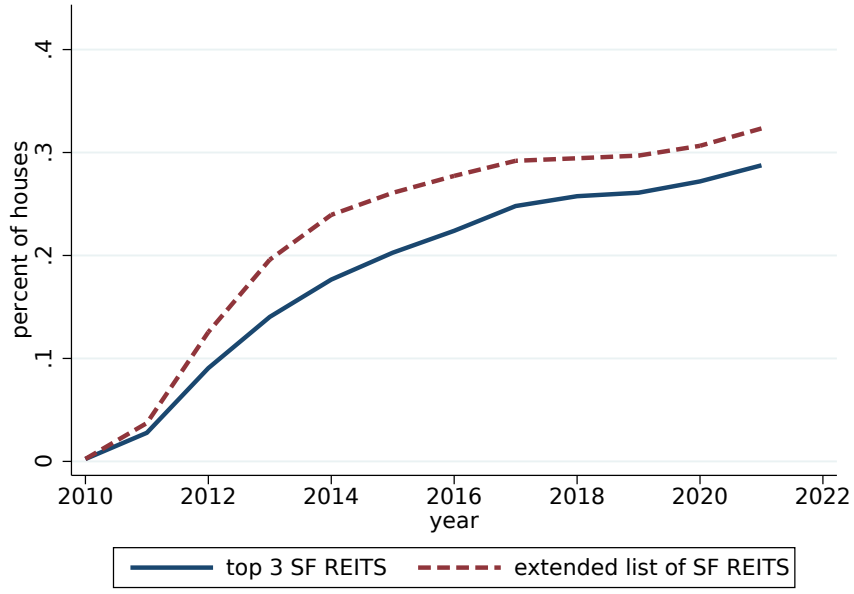
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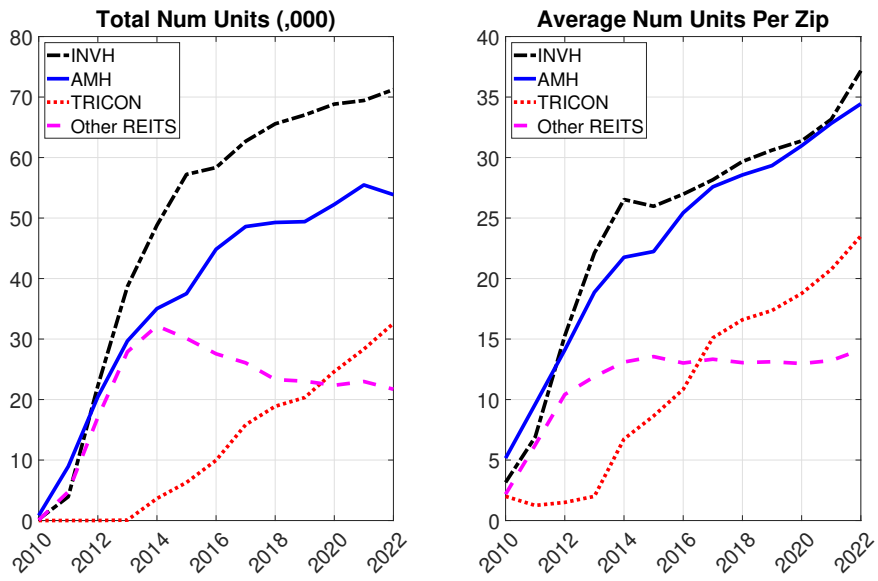


(a) Total SFR Units

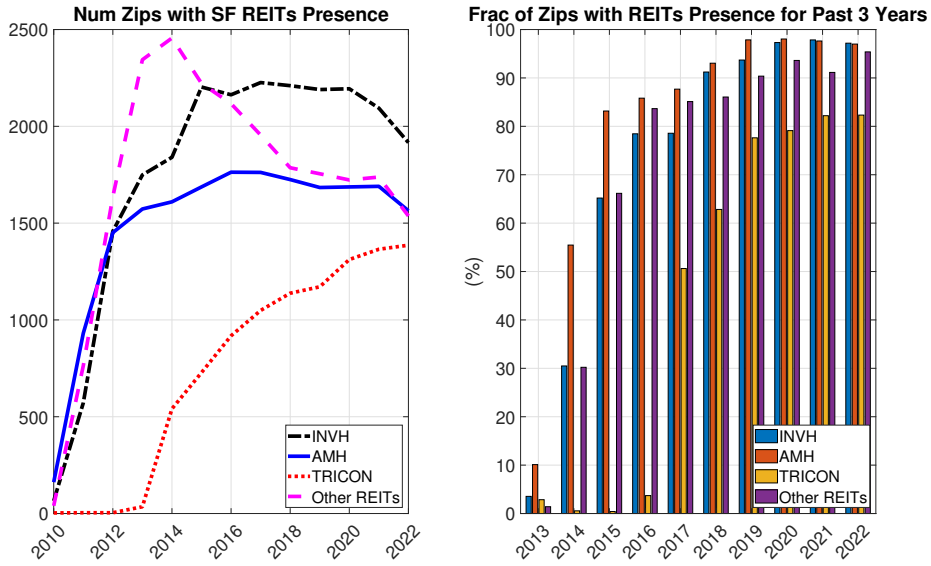


(b) Share of All SFR Units

Figure 1: This figure plots the evolution of total SFR holdings over time. Panel (a) shows the number of units owned by SFRs between 2010 and 2021. Panel (b) shows the share of single-family homes owned by SFRs between 2010 and 2021. We show results separately for the top three SFRs (INVH, AMH and TRICON) and for all SFRs. The data are from CoreLogic.



(a) Holdings across Zip Codes



(b) Market (Zip Code-Level) Penetration

Figure 2: Panel (a) of the figure shows: on the left, the total number of housing units owned by INVH, AMH, TRICON, and the other main SFRs active in the US; on the right, the average number of housing unit per ZIP code, for ZIP codes in which SFRs own at least one housing unit. Panel (b) plots: on the left, the number of ZIP codes with at least one housing unit owned by either INVH, AMH, TRICON, or the other SFRs active in the US; on the right, bars showing, out of all ZIP codes with units owned by INVH, AMH, TRICON, or other SFRs in a certain year, the fraction of ZIP codes in which the same SFRs were already present 3 years before (for example for INVH and 2013, the figure reports, out of all ZIP codes in which INVH is invested in 2013, the fraction of ZIP codes in which the REIT was already present in 2010). The data cover the sample from 2010 to 2022, and are available from CoreLogic.

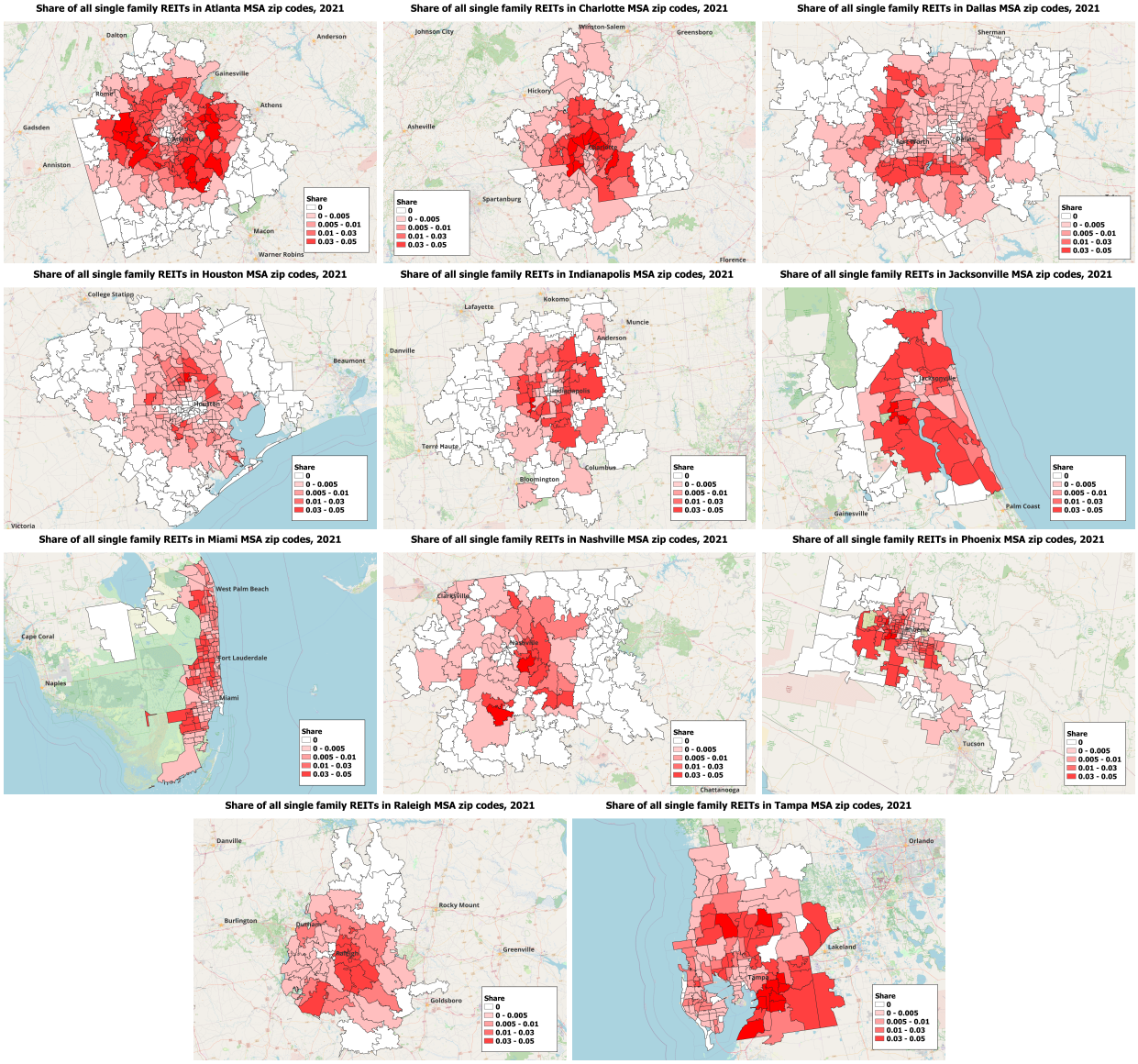
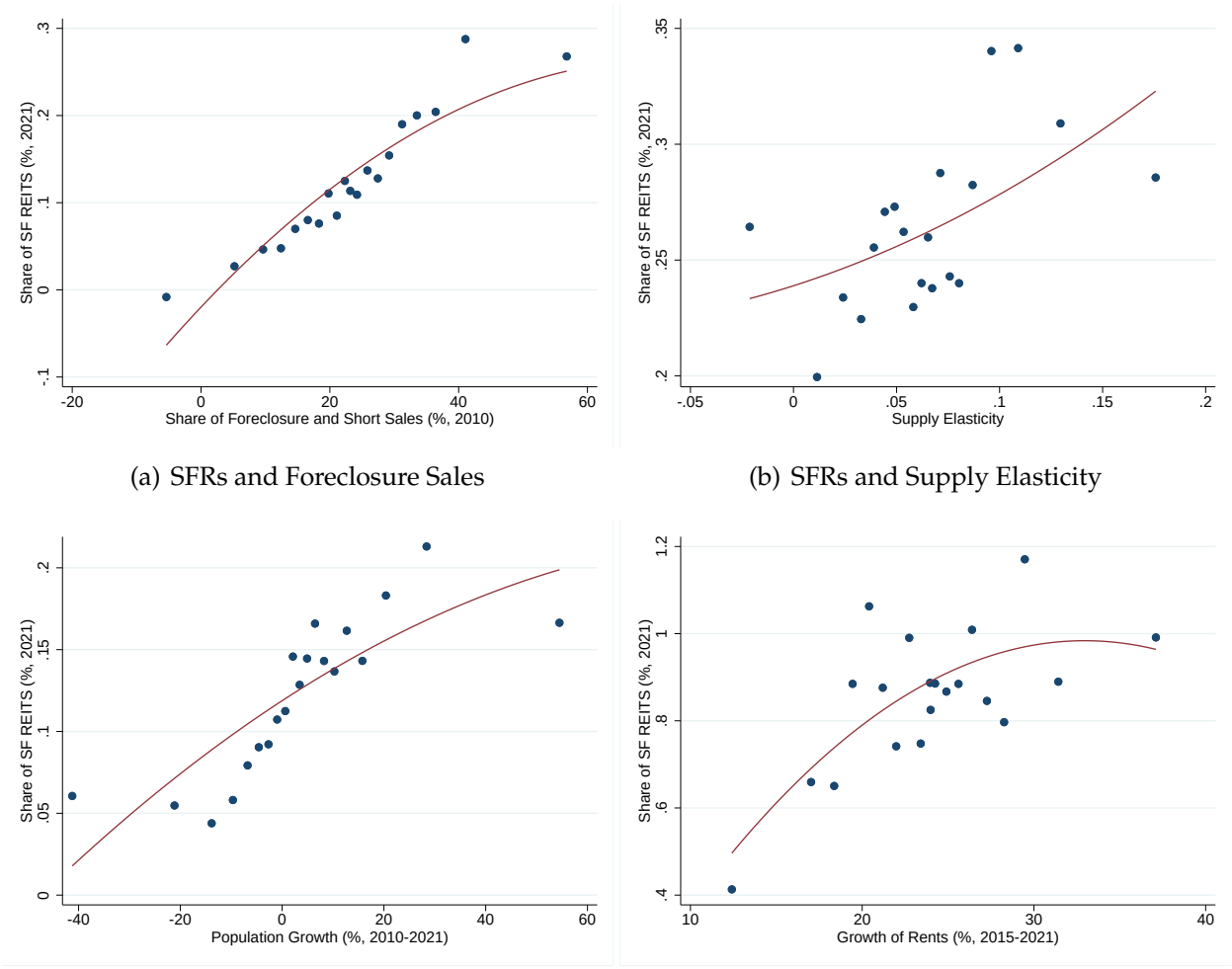


Figure 3: This figure shows ZIP code-level heatmaps of the share of single-family residences owned by SFRs in 2021, for Atlanta (GA), Charlotte (NC), Dallas (TX), Houston (TX), Indianapolis (IN), Jacksonville (FL), Miami (FL), Nashville (TN), Phoenix (AZ), Raleigh (NC), and Tampa (FL). The data are from CoreLogic.



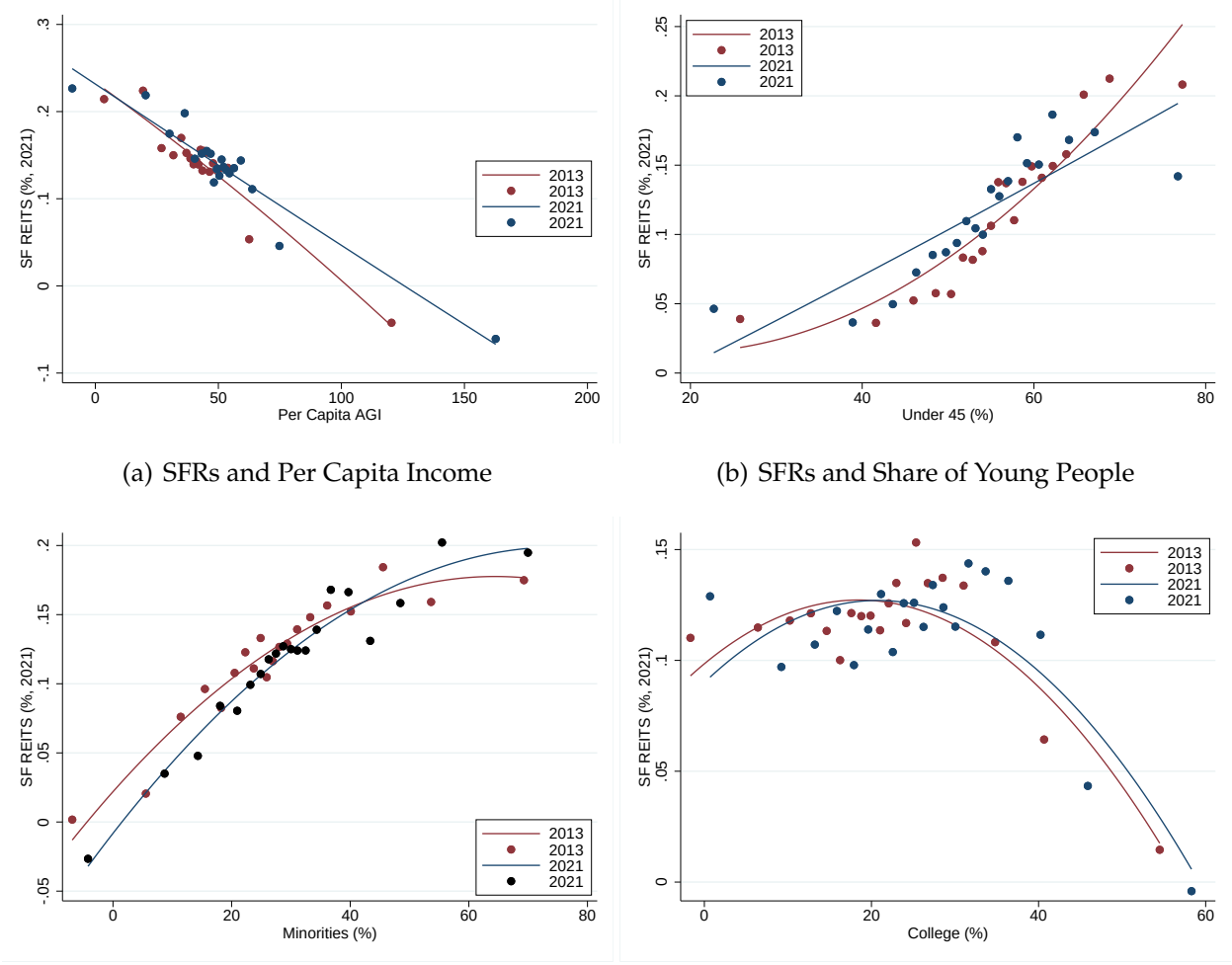
(a) SFRs and Foreclosure Sales

(b) SFRs and Supply Elasticity

(c) SFRs and Population Growth

(d) SFRs and Rent Growth

Figure 4: This figure provides bin-scatter plots of shares of single-family residences held by all SFRs at the ZIP code level in 2021 against the ZIP code level-share of single-family house foreclosure sales in 2010, supply elasticity (based on the measure developed by Baum-Snow and Han, 2024, which uses data from 2000-2010), growth in population between 2010 and 2021, and growth in rents between 2010 and 2021, respectively. County fixed effects are absorbed. The data are from CoreLogic and the Census.



(a) SFRs and Per Capita Income

(b) SFRs and Share of Young People

(c) SFRs and Share of Minority

(d) SFRs and Share of College Graduates

Figure 5: This figure provides bin-scatter plots of shares of single-family residences held by SFRs at the ZIP code level in 2021 against per capita income, the share of young individuals (under age 45), the share of minorities, and the share of population with a college degree or above. County fixed affects are absorbed. The data are from CoreLogic.

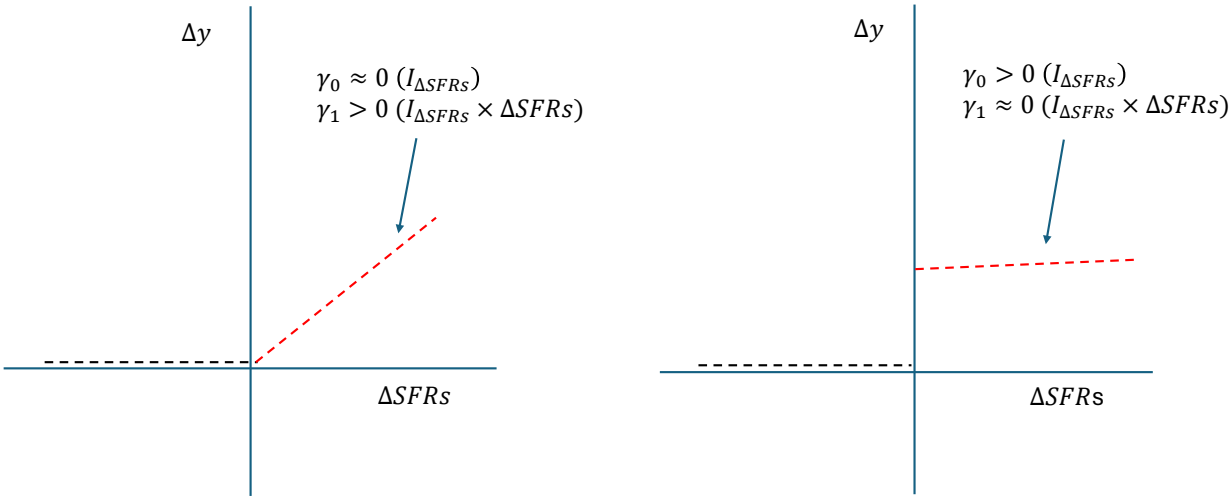


Figure 6: The figure shows two extreme cases of estimates of the coefficients γ_0 and γ_1 from equation (2). On the left, γ_0 is small and γ_1 is positive. The co-movement between an increase in the share of SFRs holdings and the outcome y grows proportionally with the increase of the SFRs share. On the left, γ_0 is positive, and γ_1 is negligible. There is a difference in the change in y, depending on whether the SFRs share increases or not. However, this effect does not depend on how large the change in the SFR share is.

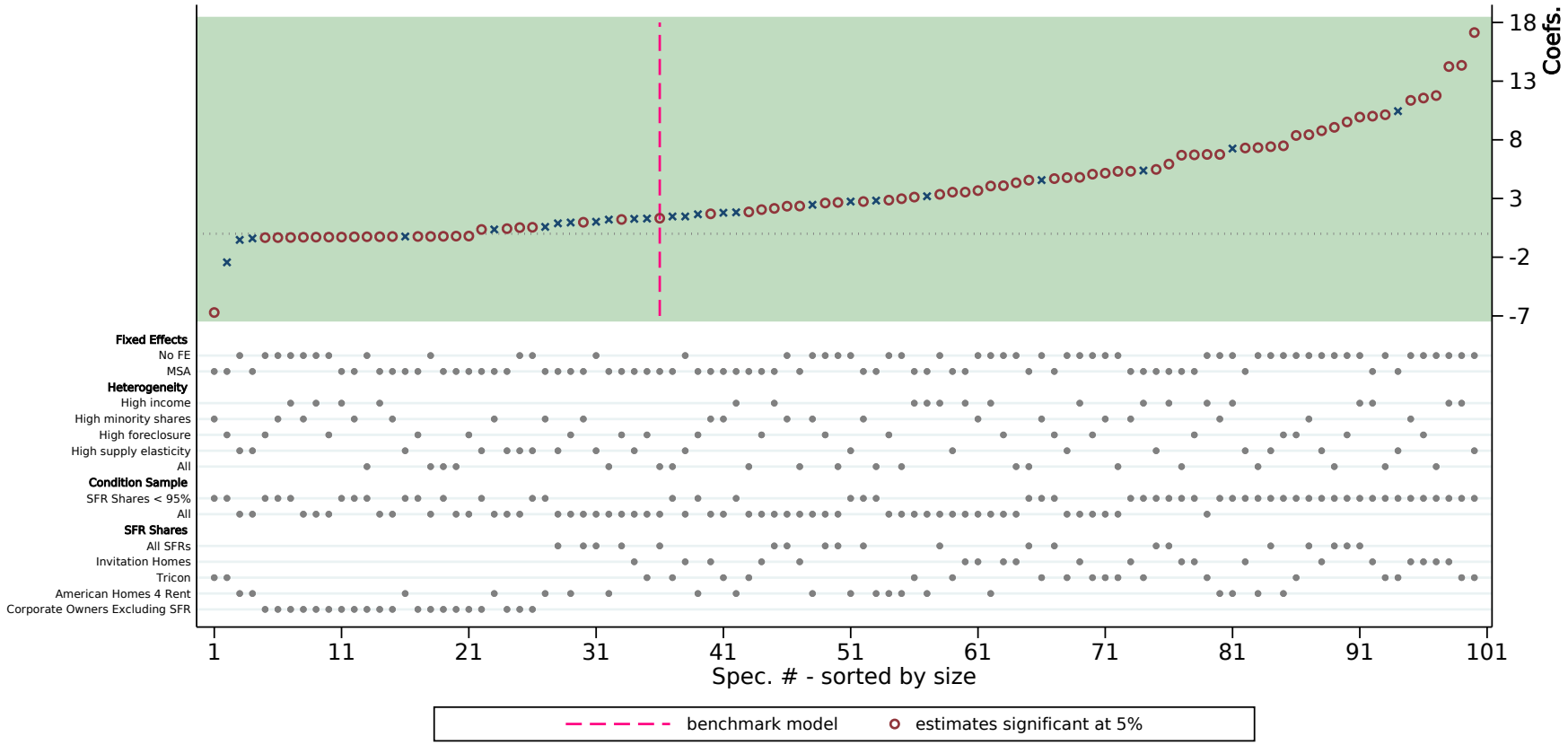


Figure 7: This figure displays the results from specification curve analysis (SCA) for regression specification having the change in housing supply as the dependent variable (panel a of Table 3). The dots are estimates of the effect of $\Delta SFRs$ on the dependent variable, and each dot corresponds to a different specification. Dots for specifications that deliver a statistically significant estimate (with 95% confidence level) are circles, while insignificant estimates are crosses.

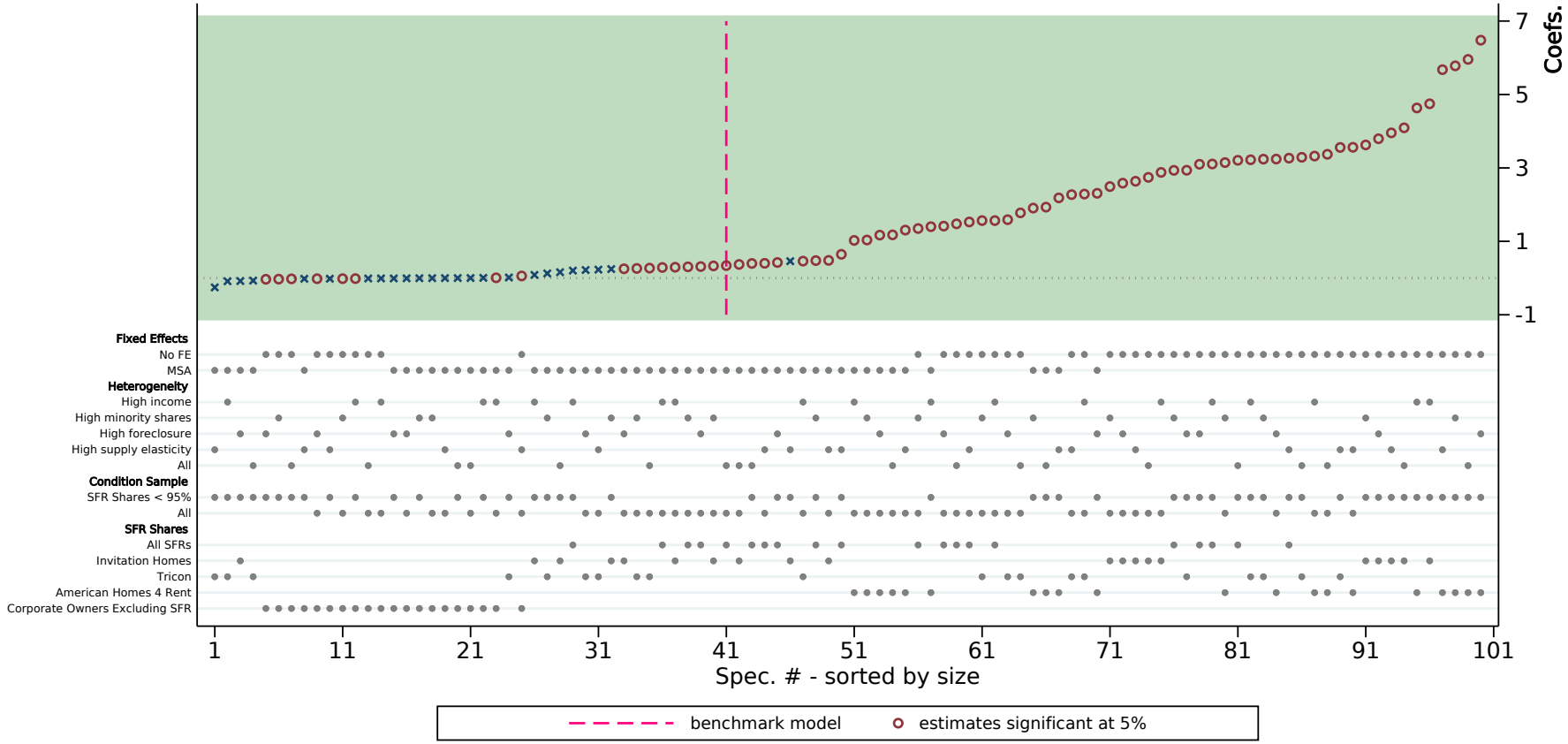


Figure 8: This figure displays the results from specification curve analysis (SCA) for regression specifications having price changes as the dependent variable (panel A of Table 4). The dots are estimates of the effect of $\Delta SFRs$ on the dependent variable, and each dot corresponds to a different specification. Dots for specifications that deliver a statistically significant estimate (with 95% confidence level) are circles, while insignificant estimates are crosses.

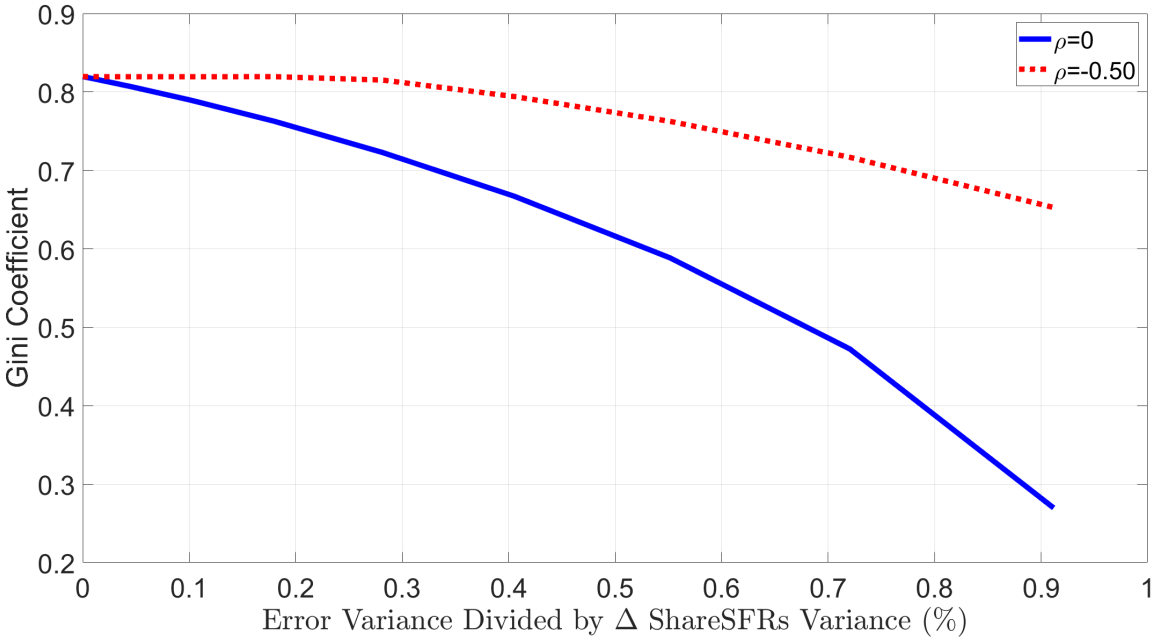


Figure 9: This figure shows the implications of measurement error in the observed change in ZIP code-level SF-REITs ownership share ($\Delta SFRs$) for the implied distribution of the latent true change ($\widetilde{\Delta SFRs}$). The x-axis displays the ratio of the variance of measurement error (σ_u^2) over the variance of the change in REITs share ($\Delta SFRs$). The y-axis plots the Gini coefficient for the implied latent change ($\widetilde{\Delta SFRs}$). The solid line shows the Gini coefficient for ρ (the correlation between u and $\widetilde{\Delta SFRs}$) is equal to zero, while the dotted line shows coefficients for ρ equal to -0.5.



(a) Dependent Variable: Change in Housing Units



(b) Dependent Variable: House Price Growth

Figure 10: This figure shows, for regressions with dependent variable equal to the change in housing units (panel a), and house price growth (panel b), the largest unbiased coefficient $\tilde{\beta}$ for $\Delta SFRs$ that can be reconciled with the (attenuated) empirical estimates in the data, for different values of the variance of measurement error (σ_u^2). The x-axis displays the ratio of the variance of measurement error (σ_u^2) over the variance of the change in REITs share ($\Delta SFRs$). The solid line reports coefficients based on simulations in which ρ (the correlation between u and $\widetilde{\Delta SFRs}$) is equal to zero, while the dotted line shows coefficients for ρ equal to -0.5.

Reported on 10-K (2021 year-end)			Matched Data	(2021 assessed year)	
Cities and States	INVH	AMH	States	INVH	AMH
Phoenix, AZ	8,172	3,147	AZ	7,440	3,886
CA	12,198	n.a.	CA	9,646	329
Denver, CO	2,348	831	CO	2,311	1,090
Large Cities of FL	24,601	6,631	FL	22,559	7,893
Atlanta, GA	12,555	4,977	GA	10,213	6,312
Chicago, IL and IN	2,630	4,543	IL, IN	718	4,319
Minneapolis, MN	1,126	n.a.	MN	1,054	1
NC, SC	4,934	8,084	NC, SC	4,758	9,784
Las Vegas, NV	3,006	1,127	NV	3,294	1,589
Columbus and Cincinnati, OH	n.a.	4,044	OH	19	3,746
Nashville, TN	16	2,907	TN	4	4,214
Large Cities of TX	4,922	8,230	TX	3,478	9,261
Salt Lake City, UT	n.a.	1,595	UT	2	1,815
Seattle, WA	3,669	n.a.	WA	3,936	1,234
Other	n.a.	6,757			
Total	80,177	52,873	Total	69,432	55,473

Table 1: This Table shows SFR holdings based on 2021 fiscal year SEC filings and on our data set, for Invitation Homes (INVH) and American Homes 4 Rent (AMH). The SEC filings report holdings by metropolitan area, while for our sample we report holdings by state. The comparison is still valid, since SFRs concentrate their holdings within major metropolitan areas. The public filings are obtained from SEC's public database EDGAR, while our data set is constructed using data from CoreLogic.

	Obs.	Mean	SD	Q05	Q25	Q50	Q75	Q95
Change in SF REITs Shares (%)	8156	0.11	0.40	-0.02	0.00	0.00	0.02	0.74
Growth in Housing Units (%, Annualized)	8156	1.43	11.85	-1.95	0.14	0.73	1.88	6.91
Growth in Units Owned by Individuals (%, Annualized)	8133	0.84	12.97	-2.28	-0.09	0.51	1.64	6.42
Growth in House Prices (%, Annualized)	4423	8.25	2.30	4.39	6.67	8.35	9.86	11.91
Change in Sale-to-List Ratio (%)	5416	4.14	4.68	-1.75	1.93	3.86	5.86	11.30
Change in Median Days on Market	5229	-64.66	139.01	-169.50	-88.00	-47.50	-14.50	18.50
Change in Purchase Mortgages Approval Rate (%)	5856	5.97	20.20	-21.67	-2.43	3.54	13.61	38.89
Change in LTV of Purchase Mortgages (%)	7073	-2.27	5.96	-10.82	-4.90	-2.23	0.37	5.96
Change in FICO of Purchase Mortgages	7150	10.78	23.30	-23.33	1.89	11.25	20.42	43.41
Average adjusted gross income (log)	7138	4.02	0.48	3.37	3.73	3.95	4.23	4.90
Share of Age 25-44	7775	0.26	0.07	0.15	0.22	0.26	0.29	0.36
Share of Age 45-64	7775	0.28	0.07	0.18	0.24	0.27	0.31	0.39
Share of Age 65 or more	7775	0.14	0.08	0.06	0.09	0.13	0.16	0.27
Share of Male	7775	0.50	0.05	0.45	0.48	0.49	0.51	0.56
Share of White	7775	0.67	0.27	0.11	0.50	0.75	0.90	0.99
Share of Black	7775	0.09	0.16	0.00	0.01	0.03	0.10	0.46
Change in Average Applicant Income (log)	5893	0.32	0.35	-0.25	0.13	0.32	0.51	0.85
Change in Average Log Loan Amount (log)	5920	0.59	0.39	-0.02	0.39	0.60	0.80	1.18
Change in Share of Conforming Loans	5920	-0.02	0.09	-0.17	-0.02	0.00	0.00	0.07
Change in Share of Primary Residence	7171	-0.01	0.12	-0.16	-0.04	0.00	0.03	0.13
Change in Share of Conventional Loans	7174	0.17	0.23	-0.21	0.05	0.18	0.30	0.50

Table 2: This table displays summary statistics of the main variables used in the empirical tests. The data are at the ZIP code level. *Change* is the difference in the values of the variable across ZIP codes from 2010 to 2021, while *Growth* is annualized percentage growth. The *Share* of individuals with different characteristics is based on 2010 data. The variables are constructed using information from Corelogic, HMDA, McDash, and the American Community Survey.

Panel A: Growth in Housing Units

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	2.17***	1.32***		1.49*
	(0.32)	(0.35)		(0.81)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			0.66*	
			(0.37)	
$I_{\Delta SFRs>0}$			0.68**	
			(0.34)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				-0.74
				(0.93)
$I_{H,SupEl}$				1.01**
				(0.45)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	8156	7137	7137	3687
R-sq	0.005	0.363	0.363	0.342

Panel B: Growth in Units Owned by Individuals

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	2.28***	1.20***		1.64*
	(0.36)	(0.36)		(0.85)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			0.41	
			(0.39)	
$I_{\Delta SFRs>0}$			0.91***	
			(0.35)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				-1.15
				(0.98)
$I_{H,SupEl}$				1.27***
				(0.47)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	8133	7132	7132	3685
R-sq	0.005	0.332	0.332	0.326

Table 3: The table reports estimates of the ZIP code-level association between the increase in the share of properties owned by single-family REITs ($\Delta SFRs_{12:21}$) and the change, between 2012 and 2021, in local housing units (panel A), and change in units owned by individuals (panel B). The specifications are as in equations 1 and 2. $I_{H,SupEl}$ is a dummy equal to one for ZIP codes with supply elasticity (based on the measure developed by Baum-Snow and Han, 2024) above median.The controls are log ZIP code income, the share of individuals of age below 25, below 45, and below 65, the share of individuals who are male, White, and Black. Results are based on data from CoreLogic.

Panel A: Growth in House Prices

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	1.35***	0.34***		0.49***
	(0.072)	(0.048)		(0.097)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			0.35***	
			(0.050)	
$I_{\Delta SFRs>0}$			0.11**	
			(0.052)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				-0.17
				(0.11)
$I_{H,SupEl}$				0.15***
				(0.056)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	4423	4395	4395	3206
R-sq	0.074	0.748	0.749	0.751

Panel B: Change in Sale-to-List Ratio

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	-1.03***	-0.48***		-0.56*
	(0.16)	(0.17)		(0.30)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			-0.54***	
			(0.18)	
$I_{\Delta SFRs>0}$			-0.0099	
			(0.16)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				0.22
				(0.35)
$I_{H,SupEl}$				-0.23
				(0.16)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	5416	5284	5284	3096
R-sq	0.008	0.197	0.197	0.308

Panel C: Change in Days on Market

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	7.16	3.53		-0.72
	(4.74)	(4.80)		(5.54)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			-2.36	
			(5.12)	
$I_{\Delta SFRs>0}$			19.5***	
			(4.58)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				1.29
				(6.23)
$I_{H,SupEl}$				-5.91**
				(2.75)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	5229	5100	5100	2960
R-sq	0.000	0.212	0.215	0.383

Table 4: The table reports estimates of the ZIP code-level association between the increase in the share of properties owned by single-family REITs ($\Delta SFRs_{2012:2021}$) and the change, between 2012 and 2021, in house prices (panel A), sale-to-list price ratio (panel B), and days on market (panel C). The specifications are as in equations 1 and 2. $I_{H,SupEl}$ is a dummy equal to one for ZIP codes with supply elasticity (based on the measure developed by Baum-Snow and Han, 2024) above median. The controls are log ZIP code income, the share of individuals of age below 25, below 45, and below 65, the share of individuals who are male, White, and Black. Results are based on data from CoreLogic and Zillow.

Panel A: Change in Purchase Mortgages Approval Rate

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	0.89	-0.38		0.68
	(0.64)	(0.74)		(1.34)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			-0.26	
			(0.79)	
$I_{\Delta SFRs>0}$			-0.49	
			(0.75)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				-1.20
				(1.52)
$I_{H,SupEl}$				0.97
				(0.72)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	5856	5784	5784	3561
R-sq	0.000	0.084	0.084	0.112

Panel B: Change in LTV of Purchase Mortgages

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	2.04***	-0.82		-0.42
	(0.71)	(0.61)		(0.91)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			-0.98	
			(0.66)	
$I_{\Delta SFRs>0}$			0.34	
			(0.61)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				-0.71
				(1.03)
$I_{H,SupEl}$				0.028
				(0.49)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	7150	6735	6735	3637
R-sq	0.001	0.271	0.271	0.373

Panel C: Change in FICO of Purchase Mortgages

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	-0.15	-0.27		-0.48**
	(0.18)	(0.16)		(0.24)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			-0.27	
			(0.18)	
$I_{\Delta SFRs>0}$			-0.020	
			(0.16)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				0.20
				(0.27)
$I_{H,SupEl}$				-0.25*
				(0.13)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	7073	6735	6735	3637
R-sq	0.000	0.328	0.328	0.481

Table 5: The table reports estimates of the ZIP code-level association between the increase in the share of properties owned by single-family REITs ($\Delta SFRs_{12:21}$) and the change, between 2012 and 2021, in the approval rate of home purchase mortgage applications (panel A), the change in the loan-to-value ratio of originated home purchase mortgages (panel B), and the change in the FICO score of originated home purchase mortgages (panel C). The specifications are as in equations 1 and 2. $I_{H,SupEl}$ is a dummy equal to one for ZIP codes with supply elasticity (based on the measure developed by Baum-Snow and Han, 2024) above median. The controls are the change in mortgage applicants log income and log loan amount between 2012 and 2021, and changes in the share of conforming, primary residence, and conventional loans between 2012 and 2021. Data come from CoreLogic and HMDA.

Panel A: Oster Bounds for Supply and Ownership

	(1) All Units	(2) Units Owned by Inds
Coeff. $\Delta SFRs_{12:21}$, *Short Regression*	2.378	2.249
Coeff. $\Delta SFRs_{12:21}$, *Long Regression*	1.322	1.201
Coeff. $\Delta SFRs_{12:21}$ Oster Bound, $R_{max} = 1.3 \times R_{long}$	0.9767	0.858

Panel B: Oster Bounds for Mortgage Access

	(1) Purchase Mtg. Approval	(2) Purchase Mtg. LTV	(3) Purchase Mtg. FICO
Coeff. $\Delta SFRs_{12:21}$, *Short Regression*	1.019	-0.155	1.841
Coeff. $\Delta SFRs_{12:21}$, *Long Regression*	-0.378	-0.266	-0.824
Coeff. $\Delta SFRs_{12:21}$ Oster Bound, $R_{max} = 1.3 \times R_{long}$	-0.812	-0.301	-1.660

Panel C: Oster Bounds for Prices and Days-on-Market

	(1) Prices	(2) Sale-to-List Price Ratio	(3) Days-on-Mkt
Coeff. $\Delta SFRs_{12:21}$, *Short Regression*	1.346	-1.00	6.178
Coeff. $\Delta SFRs_{12:21}$, *Long Regression*	0.340	-0.481	3.525
Coeff. $\Delta SFRs_{12:21}$ Oster Bound, $R_{max} = 1.3 \times R_{long}$	-0.014	-0.304	2.652

Table 6: The table reports bounds for the estimates of the coefficient β for the varialble $\Delta SFR_{z,12:21}$ in equation (1). The *Short Regression* corresponds to the specification in column (1) of Tables 3, 5, and 4, while the *Long Regression* corresponds to the specification in column (2). The bounds are based on maximum attainable R-squares equal to the R-square in the *Long Regression* multiplied by 1.3, as suggested by Oster, 2019). Estimates are based on data from Corelogic and HMDA.

Online Appendix:

Single-Family REITs and Local Housing Markets

(intended for online publication)

A1 Identifying Single-Family REITs Ownership

We follow the steps below to identify single-family REITs ownership using data from CoreLogic:

1. Using keywords to identify each company through the owner's names on the tax records from CoreLogic (*owner*_1_*full_name*, *owner*_2_*full_name*, *owner*_3_*full_name*, *owner*_4_*full_name*, and *owner_care_of_name*). For example, "AMERICAN HOME 4 RENT' is one of the keywords used to identify AMH owned properties.

2. Using the matches from step 1, use the mailing address reported on the tax records to form mailing address books for each company with the filtering below:

   (a) Mailing addresses for properties in foreclosure procedure are not used.

   (b) A mailing address is used only if at least 10 properties use that address in a state. This is to rule out some idiosyncrasy.

   (c) We manually checked each of the remaining mailing addresses and make sure they are tied to the REIT company under consideration.

3. Update the keywords for the REITs' names to capture observations of whose mailing addresses are excluded in step 2.

4. Using both keywords of owner's names and property mailing addresses to identify properties owned by each REIT company.

A2 Measurement Error Simulations

Consider the regression specification of equation (1), reproduced below:

$$y_{z,12:21} = \beta D_z + BX_z + \alpha_{Metro} + \sigma_e e_z$$

where $D_z = \Delta SFR_{z,12:21}$ is change in the share of single-family homes owned by single-family REITs in ZIP code Z, between 2012 and 2021.

In this Section, we develop a simulation exercise which addresses the concern that estimates of the coefficient of interest β might be attenuated by measurement error in D_z. We assume that measurement error has the following structure:

$$\begin{aligned} D_z &= \tilde{D}_z + \sigma_z u_z, \\ u_z &= \rho \left(\frac{\tilde{D}_z - \mu_D}{\sigma_D} \right) + \sqrt{(1-\rho^2)} v_z, \\ v_z &\overset{\text{i.i.d.}}{\sim} F\left(\frac{D_z - \mu_D}{\sigma_D} \right). \end{aligned}$$

In words, the observed variable D_z is a noisy version of the true increase in SFRs share, $\tilde{D}_z$. The noise term is u_z driven by an *i.i.d.* component v_z, drawn from the standardized empirical distribution of D_z, and has correlation ρ with $\tilde{D}_z$.

In the data, we construct $\tilde{D}_z$ as a scaled version of the observable variable D_z, as follows:

$$\begin{aligned} \tilde{D}_z &= \mu_D + S_D \frac{D_z - \mu_D}{\sigma_D}, \\ S_D &= \sqrt{\sigma_D^2 - \sigma_u^2 - \rho \sigma_D \sigma_u} \end{aligned}$$

This approach guarantees that the variance of $\tilde{D}_z + \sigma_u u_z$ is equal to the variance of D_z.

Note that given $\tilde{D}_z$, and the true unbiased value of the coefficient of interest $\tilde{\beta}$, the expected value of the dependent variable and the related residuals are:

$$\begin{aligned} \widehat{\tilde{y}}_{z,12:21} &= \tilde{\beta} \tilde{D}_z + \hat{B} X_z + \hat{\alpha}_{Metro} \\ S_e &= \sqrt{\sigma_{\tilde{y}}^2 - \sigma_{\widehat{\tilde{y}}}^2} \\ \tilde{y}_{z,12:21} &= \widehat{\tilde{y}}_{z,12:21} + S_e e_z \end{aligned}$$

The variance of $\tilde{y}_{z,12:21}$ is equal to the variance of $y_{z,12:21}$.

Our goal is to assess, given the properties of the measurement error (σ_u^2 and ρ), the maximum value of the true unbiased coefficient $\tilde{\beta}$ that can be reconciled with the attenuated estimate from the data, $\hat{\beta}$.

To this end we use the framework above, combined with a simulation and optimization algorithm. The simulation stage follows the steps below.

1. We set values of σ_u^2 (the variance of measurement error), ρ (the correlation between measurement error and the non-noisy value of the underlying independent variable), and $\tilde{\beta}$ (the unbiased value of the coefficient of interest).

2. We simulate a draw of the vector $u_{z,b}$, given values of σ_u^2 and ρ.

3. We bootstrap a draw of the vector $e_{z,b}$, given values of σ_u^2, ρ, and $\tilde{\beta}$, and calculate $\tilde{y}_{z,12:21,b} = \widehat{\tilde{y}}_{z,12:21} + S_e e_{z,b}$.

4. We estimate $\hat{\beta}_b$ from the regression equation below:

$$\tilde{y}_{z,12:21,b} = \beta_b \left(\tilde{D}_z + \sigma_z u_{z,b} \right) + B_b X_z + \alpha_{Metro,b} + \epsilon_{z,b}.$$

5. We iterate the process for $B = 100,000$ times, collect the estimates $\hat{\beta}_{b=1,\ldots,B}$, and calculate:

$$\hat{\beta}_{sim} = \hat{\beta}_{sim} \left(\sigma_u^2, \rho, \tilde{\beta} \right) = \sum_{b=1:B} \frac{1}{B} \hat{\beta}_b.$$

   This is the OLS coefficient that a researcher would recover when estimating an OLS regression, given the parameters that govern the properties of the measurement error and the unbiased value of the coefficient of interest.

Note that $\hat{\beta} \left(\sigma_{k,u}^2, \rho_k, \tilde{\beta} \right)$ increases monotonically in $\tilde{\beta}$.

We then turn to the optimization stage. We run the simulation algorithm over a fine grid of values of $\tilde{\beta}$, and find $\tilde{\beta}^*$ such that:

$$\hat{\beta}_{sim} \left(\sigma_u^2, \rho, \tilde{\beta}^* \right) = \hat{\beta},$$

where $\hat{\beta}$ is the OLS estimate of the coefficient of interest from the observational data. In words, given σ_u^2 and ρ, we find the value of $\tilde{\beta}$ that produces an OLS estimate which matches what we observe in the data.

A3 Additional Figures on the Growth of SF-REIT Property Holdings

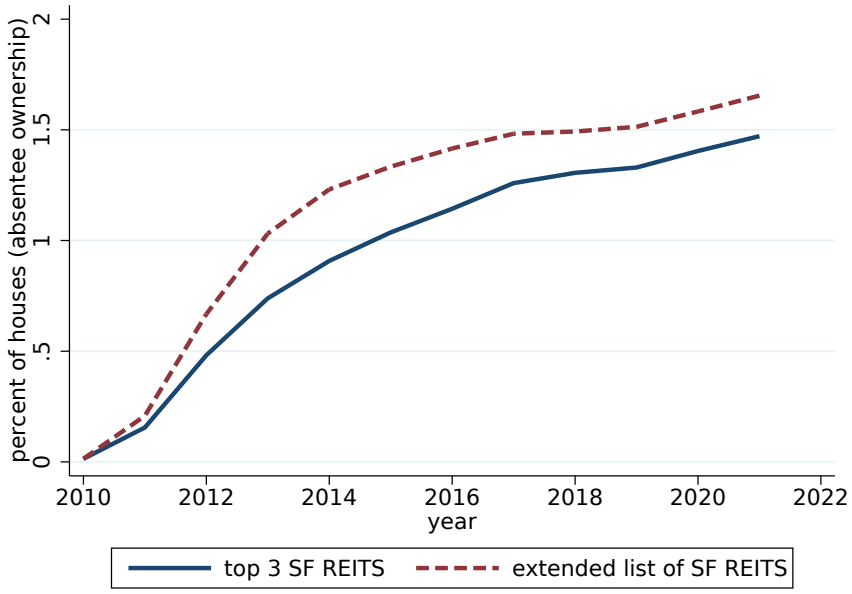


Figure A1: This Figure shows the share of single-family homes owned by SFRs between 2010 and 2021, out of all absentee owned single-family residences. We show results separately for the top three SFRs (INVH, AMH, and TRICON) and for all SFRs. The data is from CoreLogic.

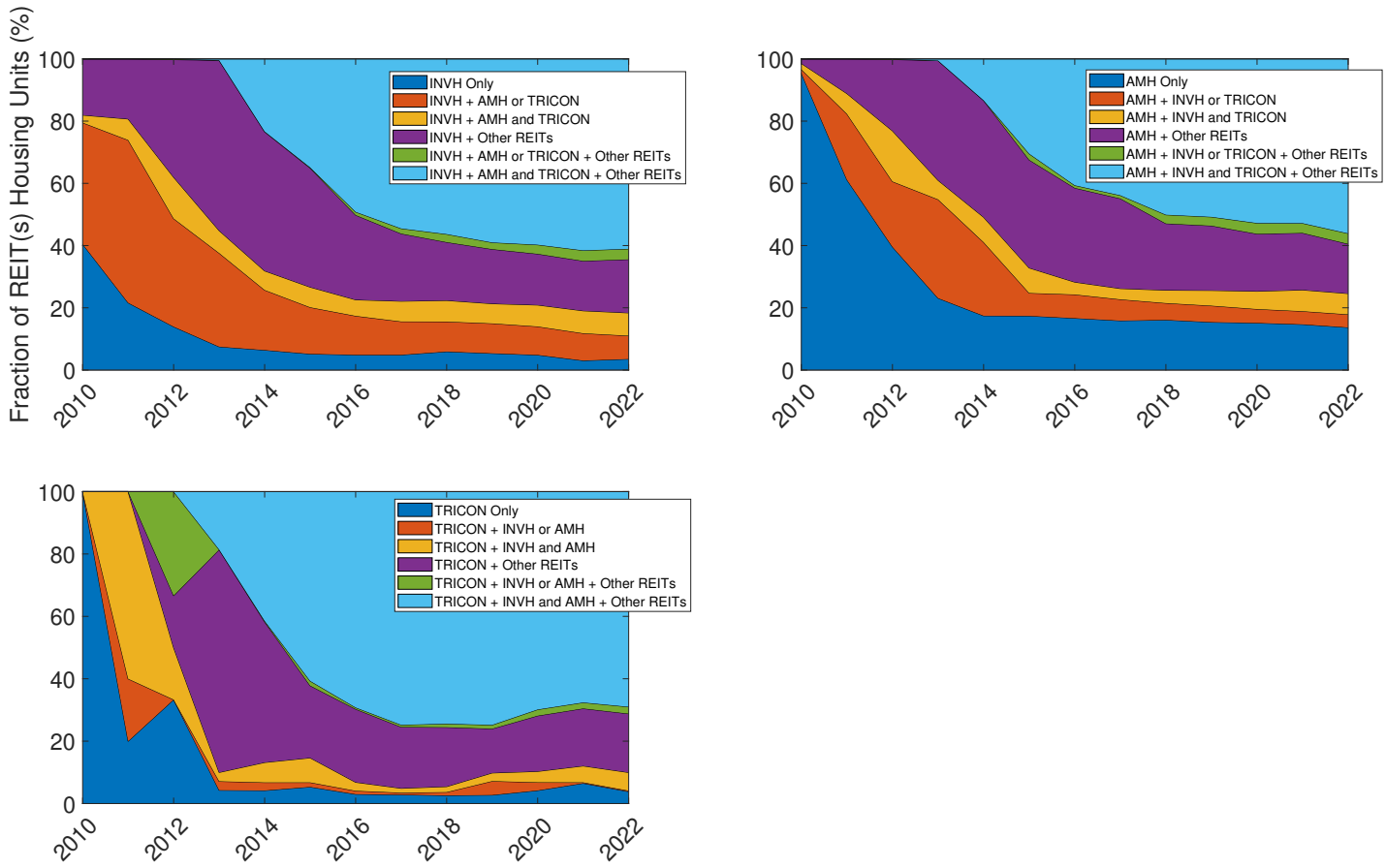


Figure A2: The figure plots the degree of overlap in the distribution of SFR assets across ZIP codes. We display 3 panels, one for each of the three largest SFRs active in the US: INVH, AMH, and TRICON. In each year, we calculate the fraction of each SFRs assets that were in ZIP codes in which it was the only REIT present, in which only the REIT and one of the other two main competitors were present, in which only the REIT and the other two main competitors were present, and so on. The data cover the sample from 2010 to 2022, and are available from CoreLogic.

A4 Additional Tables and Figures on Robustness of Measurement and Estimation

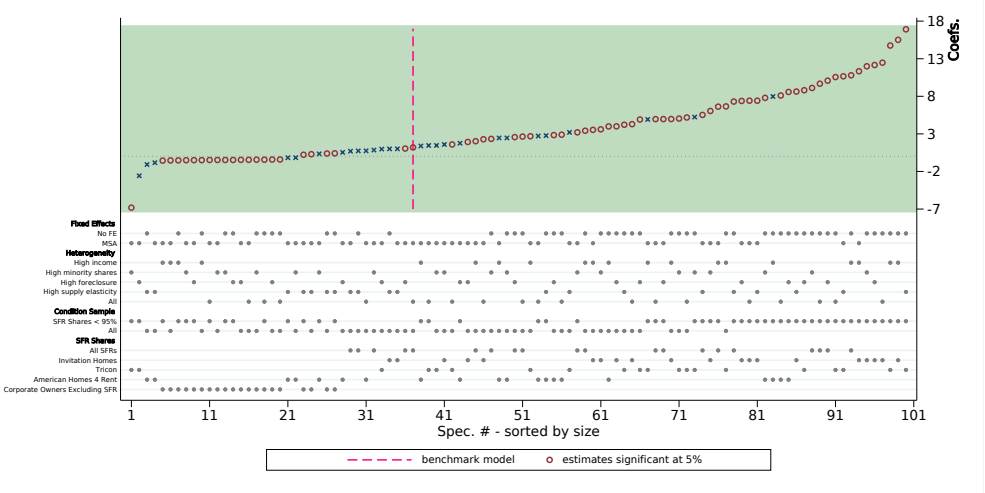
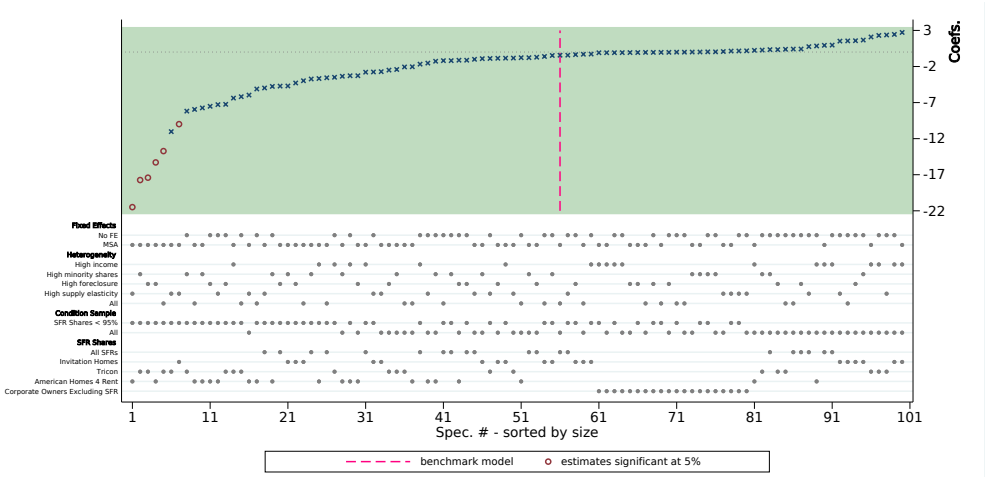
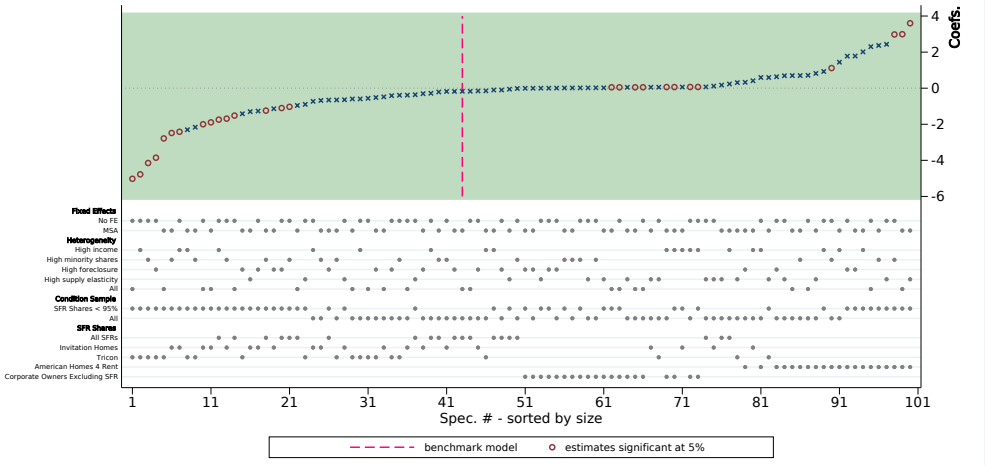


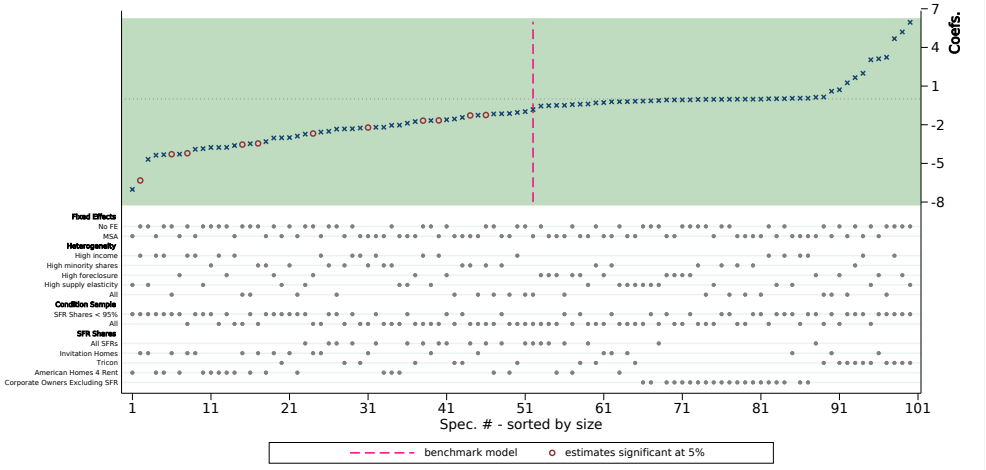
Figure A3: This figure displays the results from specification curve analysis (SCA) for regression specifications having the change in units owned by individuals as the dependent variable (panel B of Table 3). The dots are estimates of the effect of $\Delta SFRs$ on the dependent variable, and each dot corresponds to a different specification. Dots for specifications that deliver a statistically significant estimate (with 95% confidence level) are circles, while insignificant estimates are crosses.



(a) Change in Purchase Mortgages Approval Rate

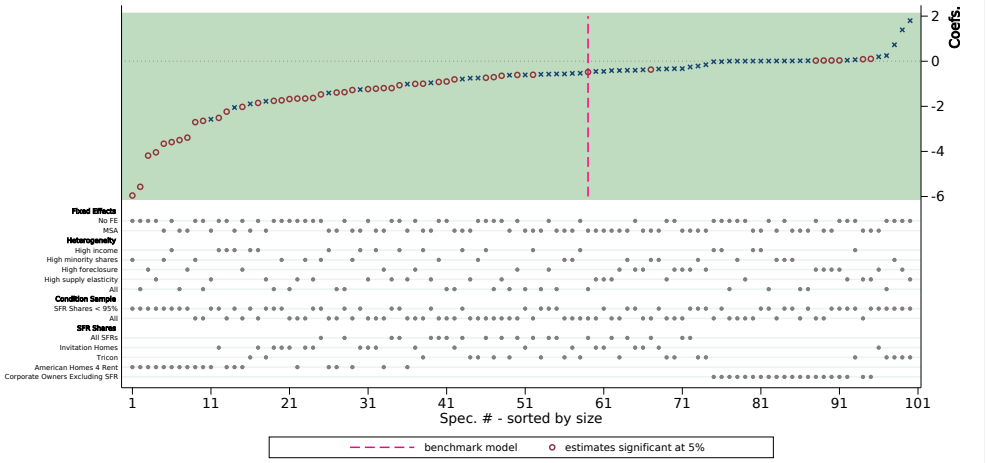


(b) Change in LTV of Purchase Mortgages

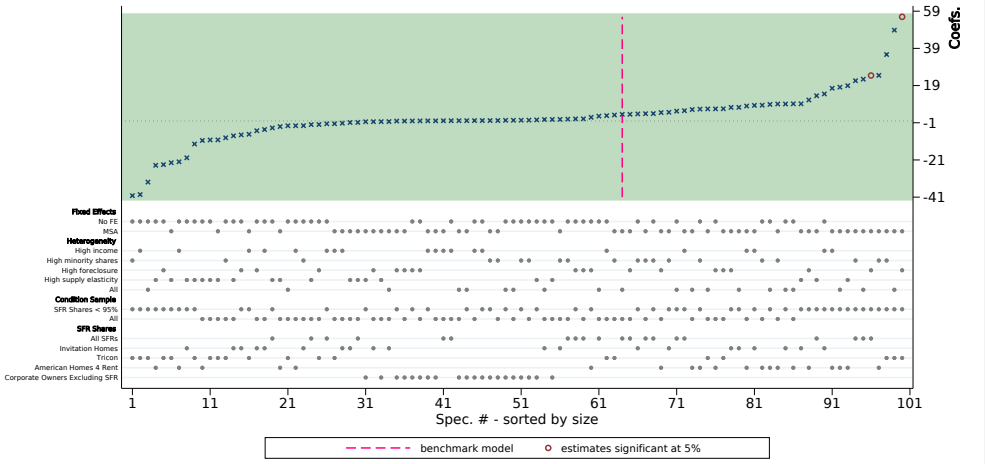


(c) Change in FICO of Purchase Mortgages

Figure A4: This figure displays the results from specification curve analysis (SCA) for regression specifications having measures of change in purchase mortgage approval rates, origination LTVs, and FICO scores (Table 4). The dots are estimates of the effect of $\Delta SFRs$ on the dependent variable, and each dot corresponds to a different specification. Dots for specifications that deliver a statistically significant estimate (with 95% confidence level) are circles, while insignificant estimates are crosses.



(a) Change in Sale-to-List Ratio

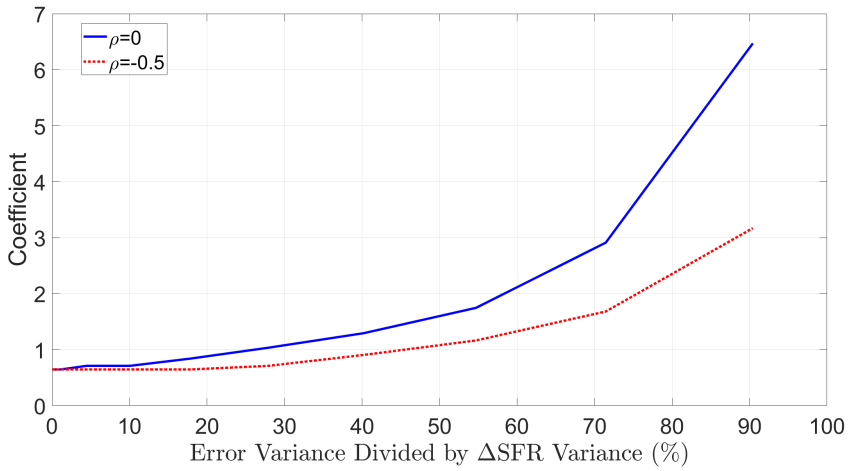


(b) Change in Days on Market

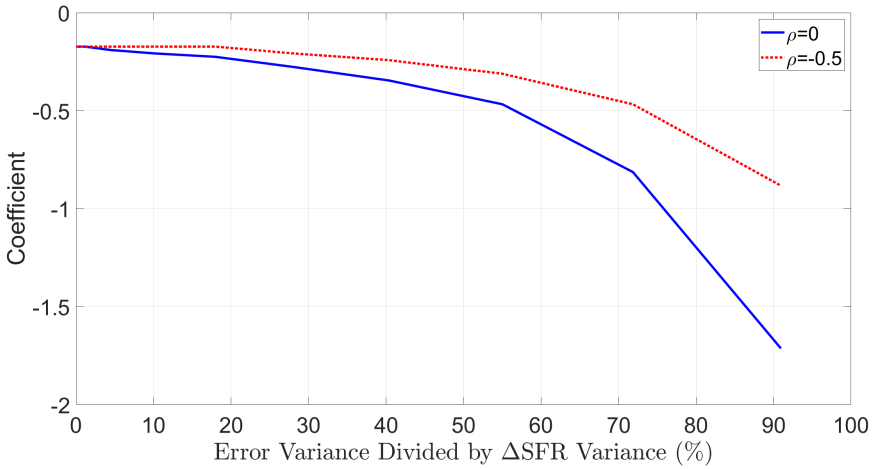
Figure A5: This figure displays the results from specification curve analysis (SCA) for regression specifications having measures of change in sale-to-list price ratio and days-on-market as the dependent variable (panels b and c of Table 4). The dots are estimates of the effect of $\Delta SFRs$ on the dependent variable, and each dot corresponds to a different specification. Dots for specifications that deliver a statistically significant estimate (with 95% confidence level) are circles, while insignificant estimates are crosses.



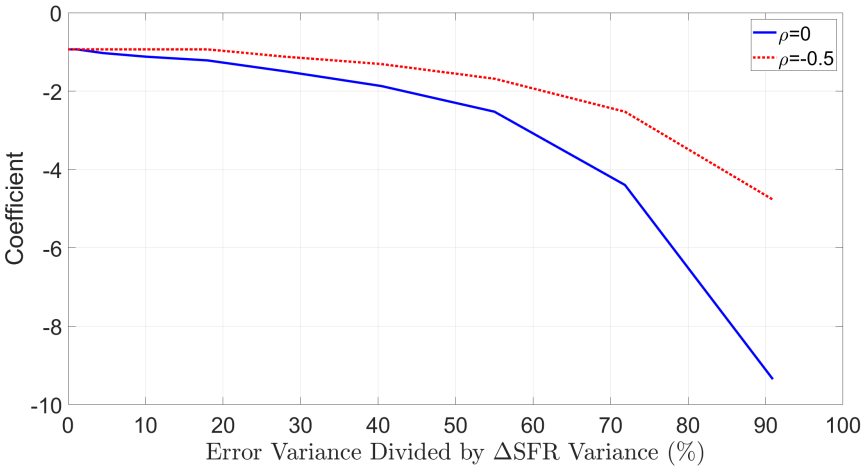
Figure A6: This figure shows, for regressions with dependent variable equal to the change in units owned by individuals, the largest unbiased coefficient $\tilde{\beta}$ for $\Delta SFRs$ that can be reconciled with the (attenuated) empirical estimates in the data, for different values of the variance of measurement error (σ_u^2). The x-axis displays the ratio of the variance of measurement error (σ_u^2) over the variance of the change in REITs share ($\Delta SFRs$). The solid line reports coefficients based on simulations in which ρ (the correlation between u and $\widetilde{\Delta SFRs}$) is equal to zero, while the dotted line shows coefficients for ρ equal to -0.5.



(a) Change in Purchase Mortgages Approval Rate

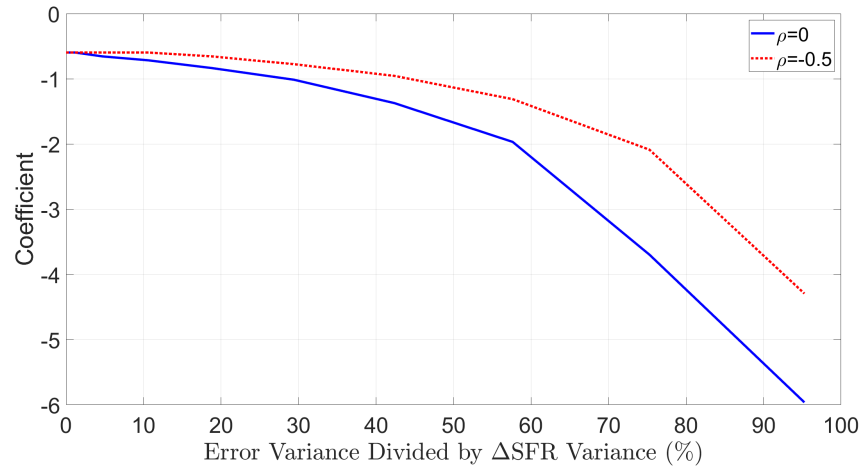


(b) Change in LTV of Purchase Mortgages

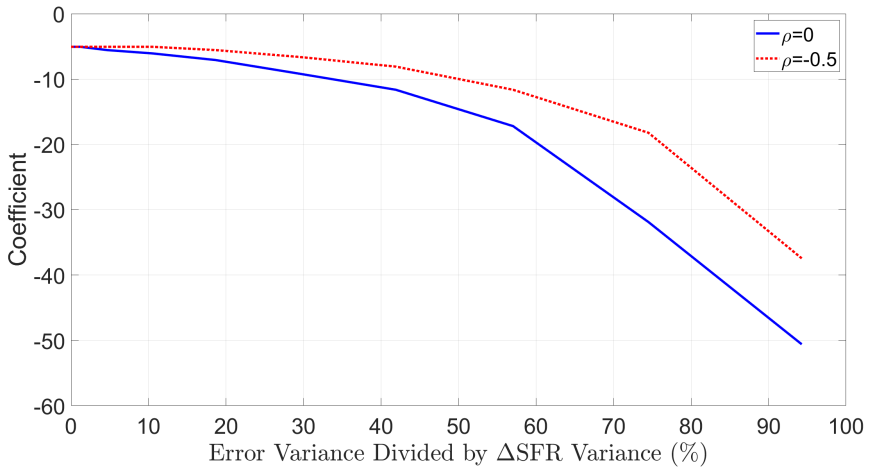


(c) Change in FICO of Purchase Mortgages

Figure A7: This figure shows, for regressions with dependent variable equal to the change in approval rates (panel a), origination LTVs (panel b), and FICO at origination (panel c), the largest unbiased coefficient $\tilde{\beta}$ for $\Delta SFRs$ that can be reconciled with the (attenuated) empirical estimates in the data, for different values of the variance of measurement error (σ_u^2). The x-axis displays the ratio of the variance of measurement error (σ_u^2) over the variance of the change in REITs share ($\Delta SFRs$). The solid line reports coefficients based on simulations in which ρ (the correlation between u and $\widetilde{\Delta SFRs}$) is equal to zero, while the dotted line shows coefficients for ρ equal to -0.5.



(a) Change in Sale-to-List Ratio



(b) Change in Days on Market

Figure A8: This figure shows, for regressions with dependent variable equal to the change in sale-to-list price ratio (panel a), and days on market (panel b), the largest unbiased coefficient $\tilde{\beta}$ for $\Delta SFRs$ that can be reconciled with the (attenuated) empirical estimates in the data, for different values of the variance of measurement error (σ_u^2). The x-axis displays the ratio of the variance of measurement error (σ_u^2) over the variance of the change in REITs share ($\Delta SFRs$). The solid line reports coefficients based on simulations in which ρ (the correlation between u and $\widetilde{\Delta SFRs}$) is equal to zero, while the dotted line shows coefficients for ρ equal to -0.5.

Panel A: Change in Mortgage Refinancing Approval Rate

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	-1.06*	-0.78		-0.016
	(0.56)	(0.65)		(1.12)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			-0.97	
			(0.70)	
$I_{\Delta SFRs>0}$			0.62	
			(0.65)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				-1.36
				(1.29)
$I_{H,SupEl}$				-0.28
				(0.62)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	6000	5936	5936	3592
R-sq	0.001	0.078	0.078	0.100

Panel B: Change in Mortgage Refinancing LTV

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	-3.31***	-1.41***		-1.47***
	(0.22)	(0.18)		(0.29)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			-1.21***	
			(0.19)	
$I_{\Delta SFRs>0}$			-0.60***	
			(0.18)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				-0.19
				(0.33)
$I_{H,SupEl}$				0.30**
				(0.15)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	7344	7045	7045	3644
R-sq	0.030	0.447	0.448	0.555

Panel C: Change in Mortgage Refinancing FICO

	(1)	(2)	(3)	(4)
$\Delta SFRs_{12:21}$	-2.44***	-2.71***		-3.39***
	(0.76)	(0.68)		(0.84)
$\Delta SFRs_{12:21} \times I_{\Delta SFRs>0}$			-2.40***	
			(0.73)	
$I_{\Delta SFRs>0}$			-0.96	
			(0.67)	
$\Delta SFRs_{12:21} \times I_{H,SupEl}$				-0.49
				(0.96)
$I_{H,SupEl}$				-0.50
				(0.45)
Controls	NO	YES	YES	YES
MSA FE	NO	YES	YES	YES
N	7367	7045	7045	3644
R-sq	0.001	0.194	0.194	0.352

Table A1: The table reports estimates of the ZIP code-level association between the increase in the share of properties owned by single-family REITs ($\Delta SFRs_{12:21}$) and the change, between 2012 and 2021, in the approval rate of refinancing mortgage applications (panel A), the change in the loan-to-value ratio of originated mortgage refinancings (panel B), and the change in the FICO score of originated mortgage refinancings (panel C). The specifications are as in equations 1 and 2. $I_{H,SupEl}$ is a dummy equal to one for ZIP codes with supply elasticity (based on the measure developed by Baum-Snow and Han, 2024) above median. The controls are the change in mortgage applicants log income and log loan amount between 2012 and 2021, and changes in the share of conforming, primary residence, and conventional loans between 2012 and 2021. Results are based on data from CoreLogic and HMDA.