

House Prices, Investors, and Credit in the Great Housing Bust

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Abstract

What role did investors play in stabilizing housing markets during the Great Housing Bust? Using transaction-level data, I distinguish between two distinct classes of housing investors: large, deep-pocketed corporate investors, and small household investors that rely on mortgage credit. I estimate that in response to a negative mortgage credit supply shock, house prices fell by 30 percent more in markets where household investors absorbed a larger share of house purchases than did corporate investors. To rationalize this result, I build a heterogeneous agent model of the housing market featuring both types of investors. The model maps the estimated relative decline in house prices to the relative housing demand elasticities of corporate and household investors. Because household investment is relatively inelastic, the model produces a much larger equilibrium decline in house prices in response to a negative mortgage credit supply shock when household investors are the marginal house buyers. I show that the lower household investment demand elasticity is due to household exposure to the mortgage shock, the illiquidity of housing assets, and losses on primary property wealth. When corporate investors are the marginal house buyers during the shock, house prices are more stable and household welfare improves. This is the case even though homeownership rates fall by more and capital gains on housing during the recovery accrue to firms rather than households.

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1. Introduction

The 2000s housing boom ended in a Great Housing Bust, featuring sharp contractions in mortgage credit and rapidly declining house prices. Homeownership rates fell from historic peaks as household demand for housing declined. But as prices fell, returns on housing rose for those who could buy and hold properties for the duration of the bust. Greater returns presented investment opportunities for many buyers. And although housing market activity slowed overall, an increasing share of the properties sold during this period were purchased by housing investors.

In this paper, I study the investment stabilization channel of housing markets in response to a negative housing demand shock. I show that while investors help to dampen the decline in house prices, the strength of this channel depends on certain characteristics of the investors themselves. I argue that the elasticity of housing investment demand differs significantly across two distinct classes of investors that were active in housing markets during the bust: corporate and household investors. While corporate buyers behave like large and deep-pocketed investors, household investors are small and often rely on mortgage credit to finance their purchases. Thus, a mortgage credit contraction exacerbates differences in the ability of these investors to help stabilize housing markets. And variation in the composition of these investors across markets may help account for the large variation in house price declines observed during the housing bust.

I first present empirical estimates of the effect of investment on house prices in response to exogenous changes in mortgage credit. I find that an increase in the share of corporate investor purchases is associated with a 30 percent smaller decline in house prices than a similar sized increase in the share of household investor purchases. In the second part of the paper, I rationalize this result using a structural macroeconomic model of the housing market that features both types of investors. The model is calibrated to reproduce the estimated relative decline in house prices associated with each type of investor. I then show that the lower elasticity of household investment demand is accounted for by their exposure to changes in mortgage credit conditions, the illiquidity of housing assets, and fluctuations in wealth due to changes in the value of primary property. While corporate investment activity is associated with much more stable house prices, the higher elasticity of investment demand results in a much larger reallocation of the housing stock towards investors, and a much larger decline in the homeownership rate. Nevertheless, household welfare is higher in the more stable economy with more elastic corporate investment activity.

For the empirical analysis, I use housing transaction data from the Zillow Transaction and Assessment database (ZTRAX) to study housing investment activity during the bust. This detailed micro-data shows that corporate and household investors differ in important aspects of their investment behavior. For example, corporate investors buy many more properties than do household investors, corporate investors trade properties far more frequently than do household investors, while household investors are far more likely to use mortgage debt to finance their purchases. These stylized facts suggest that investors may have very different elasticities of investment demand.

I argue that a combination of cross-sectional data on house prices, investment activity, and exogenous shocks to housing demand can be used to infer the elasticities of housing investment. To do this, I employ an instrumental variables regression strategy using zip code-level panel data for the housing bust period from 2006 to 2010. I proxy for local housing demand shocks using exogenous changes in mortgage credit, where I use an instrument constructed from the share of mortgages sold to non-government sponsored enterprises (GSEs) in secondary mortgage markets prior to the housing boom and bust. This instrument resembles a mortgage credit supply shock, since the rapid rise in non-GSE activity during the housing boom was associated with increases in mortgage borrowing and decreases in mortgage interest rates (see Mian et al., 2009; Justiniano et al., 2017; Mian et al., 2018). As non-GSE activity contracted from 2006, housing markets that were more exposed to mortgages originated and sold to non-GSEs experienced a larger decline in mortgage credit and thus larger shocks to housing demand.¹

Instrumental variable regression results show the effect of mortgage credit on house prices and how that effect is moderated by changes in the investment shares of house purchases. I find that on average, a one standard deviation decline in mortgage credit is associated with an 8.5 percent decrease in house prices during the housing bust. However, I find that prices decrease just 5.2 percent in markets facing a one standard deviation increase in the corporate investor share. Whereas prices decline 7.4 percent in markets facing a one standard deviation increase in the household investor share. Overall, an increasing share of corporate investors is associated with a 30 percent smaller house price decline than a similar sized increase in the share of household investors.

To rationalize these empirical results, I build a structural macroeconomic model of the housing market to study equilibrium responses to mortgage credit shocks. Following the recent macro-housing literature, the core of the model features heterogeneous, life-cycle households who face uninsurable income risk, rent or buy houses, and use long-term mortgage debt to finance house purchases (see, for example, Favilukis et al., 2017a; Kaplan et al., 2017; Greenwood, 2018; Garriga et al., 2018). I also introduce roles for both household and corporate housing investors. Household investment is endogenously determined, as households may choose to buy investment properties in addition to the houses in which they live. Unlike owner-occupied property, investment property generates rental income subject to a cost associated with being a landlord. But like owner-occupied property, investment properties are traded subject to transaction costs and can be used as collateral for mortgage borrowing. Corporate investment comes from a representative, deep-pocketed, risk-neutral firm that maximizes profits generated by leasing properties in the rental market as well as trading those properties in the housing market. Corporate investors face a convex portfolio holding cost, which captures decreasing returns to scale for residential housing investment in reduced form (see Mills et al., 2019). The curvature

¹The mortgage credit instrument is constructed using Home Mortgage Disclosure Act (HMDA) data. A better measure of exposure to the mortgage credit supply shocks of the mid-2000s might come from mortgages sold directly into private label securitization (PLS), rather than to non-GSEs. However, the HMDA data appears to significantly undercount PLS mortgage purchases in the secondary market, as can be seen by comparing to the measures of total PLS activity reported in Justiniano et al. (2017). Nevertheless, in Section 4.4 I show that the main results are robust to using the more direct PLS measure.

of this function is governed by the elasticity of corporate investment demand with respect to housing returns.

The model is calibrated to match key features of the US housing market prior to the the 2000s housing bust. I then use the model to study equilibrium responses to an exogenous, unexpected, temporary contraction of mortgage credit. The shock consists of an increase in the mortgage interest rate, an increase in mortgage origination costs, and a tightening of mortgage borrowing constraints (see Justiniano et al., 2015; Favilukis et al., 2017a; Greenwald, 2018). Since homeowners are both dependent on mortgage credit and hold most of the housing stock in steady state, the primary effect of the shock is to decrease homeowner demand for housing. This causes a decrease in equilibrium house prices, but the size of the decline depends on the characteristics of the marginal house buyer following the shock. By varying the elasticity of corporate investment demand, I can alter the concentration of corporate investors in the housing market which changes the marginal house buyer following the shock. For high (low) elasticities, the model generates equilibria in which corporate (household) investors purchase an increasing share of houses and there are small (large) declines in house prices.

I compare two housing markets: one in which the corporate elasticity is zero, and one in which the elasticity of corporate investment is calibrated to match the estimated relative decline in prices across investors. The model generates price declines in the economy with elastic corporate investors that are 30 percent smaller on impact and 45 percent smaller four years into the housing bust. I show that the economy with corporate investors results in more stable house prices, networth, consumption, and higher household welfare. This latter is despite the fact that corporate profits do not accrue to households and that homeownership rates decline by more (see Lambie-Hanson et al., 2019).

The relatively low elasticity of household investment demand helps account for the large decline in house prices observed in many housing markets across the US during the housing bust. For this reason, I use the model to explore the factors that account for the insensitivity of household investment to changes in house prices. I study three primary explanations. First, unlike corporate investors, households looking to finance investment face rising costs of mortgage credit during the housing bust. Since nearly 60 percent of household investors hold mortgage debt in the steady state of the model, rising mortgage costs reduce the return to housing investment for most of these investors. In a partial equilibrium exercise, I show that the household investor share of house purchases falls during the course of the shock, and investment ownership rates decline by 23 percent over the first five years. Second, household investors face transaction costs when trading housing assets, which reduces the incentive to invest. In partial equilibrium exercises, I find that household investors are much more sensitive to the capital gains earned by housing than the higher rental income generated in response to the shock. Since all house sales in the model are subject to transactions costs, this weighs most heavily on the component of returns to housing that most motivates household investment. In a general equilibrium experiment where I temporarily eliminate the transaction cost associated with investment property sales, I show that the household investor share of purchases rises by 10 percentage points, investment ownership rises by more than two percentage points, and house prices fall by 25 percent less at the trough. This suggests that a liquidity premium on housing

accounts for around half of the price decline associated with household investors relative to corporate investors. Third, since households invest in the same housing market in which they own primary property, the decline in house prices that makes investment attractive also reduces the value of existing housing wealth. For example, in the model where household investors are the marginal house buyers, I show that the median homeowner experiences a 12 percent decline in networth in the first period following the shock. In a partial equilibrium exercise where I hold the value of primary property constant following the shock, I show that the rate of investment ownership rises relative to the baseline case. Thus, losses on primary property are another important source of households' unwillingness to invest during the housing bust.

2. Related literature

Several papers have studied the role of household investment in housing during the 2000s housing boom. Using administrative data on credit records, Haughwout et al. (2011) show that household investors made up an increasing share of mortgage borrowing from 2000 to 2007. Adelino et al. (2016) argue that much of the additional mortgage debt generated by the housing boom flowed to middle-income households who borrowed for investment purposes. Mian et al. (2018) tie the rise of household borrowing for investment directly to the increase in mortgage credit supply of the mid-2000s. They show that cities that were more exposed to mortgage credit supply shocks experienced a larger increase in household investment activity. Garcia (2019) uses geographic exposure to vacation homes as an instrument for housing investment activity and shows that household investment amplified house prices during the housing boom. Haughwout et al. (2011), Adelino et al. (2016), and Mian et al. (2018) all show that the increase in household investor borrowing during the housing boom was strongly associated with mortgage defaults by household investors during the bust. These results all suggest that household investment activity is particularly sensitive to mortgage credit conditions. In the current paper, I show that the sensitivity of household investment to mortgage credit helps explain the lower elasticity of investment demand during the housing bust. This helps account for the larger house price declines observed in housing markets that substituted homeowner housing demand for household investment rather than corporate investment.

Several recent papers have studied the effects of corporate investment on housing markets. Lambie-Hanson et al. (2018) and Mills et al. (2019) document that large, institutional investors purchased a large and increasing share of houses during the housing bust. Mills et al. (2019) attributes some of this increase to the entry of large buy-to-lease investors in the late 2000s. They provide OLS regression evidence that these corporate investors supported house prices during the housing bust in those neighborhoods in which they were most active. Lambie-Hanson et al. (2019) study the effect of corporate investment on house prices using an instrumental variables regression design that exploits changes in policies that favored purchases of foreclosed properties by household investors over corporate investors during the housing bust. They find that higher corporate investment activity is associated with higher house prices and lower homeownership rates. I confirm this effect of corporate investment activity on local house prices

during the housing bust. Where I differ from Lambie-Hanson et al. (2019) is in showing that corporate investment activity dampens house price declines specifically in those housing markets that were subject to negative mortgage credit shocks. I also expand the analysis to consider the effect of corporate housing investment relative to household investment, which is shown to have much weaker effects on house prices. Like the analysis in Mills et al. (2019) and Lambie-Hanson et al. (2019), but unlike the literature studying the effects of household investment, I use housing transaction data rather than credit records to identify investment activity. As I show in Section 3, this is particularly important during the housing bust because the share of investors using a mortgage declined much faster than the share of homeowners using a mortgage. Because credit records do not report non-mortgaged house purchases, this data would incorrectly observe a decline in housing market investment activity in many housing markets where it in fact increased.

In the empirical analysis of this paper, I use mortgage credit shocks to shift homeowner demand for housing. In response to these demand shifts, the decline of house prices and the increase in housing investment activity help to identify the elasticity of housing investment demand. Following much of the literature, I use mortgage credit supply shocks as instruments to study the response of house prices to fluctuations in mortgage credit. I follow Mian et al. (2009) and Mian et al. (2018) in constructing local exposures to non-GSE activity in the secondary mortgage market. As discussed in Mian et al. (2009), Justiniano et al. (2017), and Mian et al. (2018), the boom and bust in non-GSE mortgage purchases in the 2000s closely resembled a mortgage credit supply shock given the associated decline in mortgage interest rates, rise in mortgage originations, and shift towards ex-ante riskier borrowing. I report similar estimates of the average effect of mortgage credit on house prices as recent estimates in Favara et al. (2015), Mian et al. (2018), and Greenwald et al. (2019).

Following the empirical results, I build a macroeconomic model of the housing market to study the equilibrium relationship between mortgage credit, investors, and house prices. The model follows a large recent literature that models the 2000s housing boom and bust (see Iacoviello et al., 2013; Chen et al., 2013; Landvoigt et al., 2015; Hedlund, 2016; Hurst et al., 2016; Favilukis et al., 2017a; Kaplan et al., 2017; Berger et al., 2017; Greenwald, 2018; Garriga et al., 2018; Garriga et al., 2019; Diamond et al., 2019; Greenwald et al., 2019). Most of these models have in common a heterogeneous household structure that captures several important features of households' interactions with housing markets: income risk, illiquid housing, and long-term mortgage debt. The models are then used to account for different aspects of the housing boom and bust by studying equilibrium responses to mortgage credit expansions and contractions.

Guerrieri et al. (2017b) presented an early of experiment of this form, studying the effect of tightening household borrowing constraints.² However, to the extent that a consensus is forming in this literature, it is that a tightening of credit constraints could not have generated the housing boom and bust on its own. Justiniano et al. (2015) argue that in isolation looser constraints lead to an increase in borrowing and higher interest rates in equilibrium, contrary

²An earlier version of that paper circulated in Guerrieri et al. (2011).

to the declining interest rates observed during the housing boom. Greenwald (2018) shows that changes in mortgage payment to income constraints, in addition to loan to value constraints, are important for amplifying the effects of interest rate changes. Favilukis et al. (2017a) show that to generate a house price boom their model needs aggregate risk to affect housing risk-premia, which in turn drives fluctuations in housing demand. Kaplan et al. (2017) argue that the magnitude of the housing boom requires fluctuations in beliefs about future housing demand to influence contemporaneous housing demand.

In this paper, I add to the literature by studying the role of housing investment during the housing bust. To do this, I introduce both household and corporate investors into an otherwise standard model of the housing market. I show that the marginal investor in the housing market during a mortgage credit contraction determines the elasticity of housing investment demand, which in turn explains the magnitude of the decline in house prices. In a recent paper, Greenwald et al. (2019) also study the influence of housing investment on housing markets during this period. They show that the degree of segmentation between housing markets for rental and owner-occupied property is important for explaining how credit affects housing demand. In the current paper, I assume no segmentation in housing markets, but concentrate on the demand elasticity of the marginal house buyer at the time of the shock. Additionally, Greenwald et al. (2019) present a model with limited household heterogeneity, whereas I study a model with endogenous housing and investment choices, life-cycle dynamics, idiosyncratic income risk, and incomplete markets, which generates significant dispersion in housing wealth and indebtedness. I show that relatively wealthy households choose to become investors, which accounts for their ability to continue to buy houses during a shock. However, despite being wealthy many household investors also rely on mortgage debt to finance their purchases. This both accounts for why household investment is sensitive to changes in mortgage credit, and for why the elasticity of household investment is lower than for unconstrained corporate investment.

I model housing markets as featuring renters, homeowners, household investors, and corporate investors. Households may buy investment properties that are separate from their primary property. Both types of investors buy and sell properties in the housing market, and lease their properties to renters in the rental market. Finally, the elasticity of corporate investment depends on a (calibrated) convex portfolio holding cost. This approach is more general than many of the models presented in the literature. Favilukis et al. (2017a) abstract from the rental market altogether. Kaplan et al. (2017) model renters whose property demand is satisfied by a perfectly elastic corporate rental firm. In a model studying the relationship between tax and homeownership, Chambers et al. (2009a) allow homeowners to lease a fraction of their primary property to renters. They also introduce corporate landlords who do not trade property, but instead produce rental services from consumption goods and are sensitive only to changes in rental rates.³ Favilukis et al. (2017b) study out-of-town housing investment demand in a model with both landlord households and out-of-town housing investors. All housing wealth in Favilukis et al. (2017b) is liquid suggesting fairly elastic household investment demand. Out-of-town investors are modeled as a source of inelastic housing demand, where these buyers hold properties but

³Sommer et al. (2018) abstract from corporate landlords but also allow homeowners to lease a share of their homes to renters.

do not lease them to renters in the rental market.

3. Data

3.1. Housing Data

Housing transactions data come from the Zillow Transaction and Assessment Dataset (ZTRAX), made available by Zillow Research.⁴ The full ZTRAX dataset contains more than 370 million transactions from across the US. It draws on deed records to report information on transactions, prices, mortgages, property characteristics, and geographic information for residential and commercial properties. I restrict analysis to transactions for regular sales of residential, single-family houses. Regular sales exclude forced or foreclosure sales, intra-family transfers or gifts, and transactions with builders, developers, or real estate agents on either side of the transaction.

For the purposes of this analysis, I drop all transactions with missing buyer addresses or missing buyer description information. Reliable ownership information is not available in every location, so I restrict the analysis to data from those states in which I observe buyers' addresses for at least 85 percent of transactions. These states are: Alaska, Arizona, California, Colorado, Delaware, Florida, Iowa, Idaho, Indiana, Hawaii, Kentucky, Maryland, Minnesota, Missouri, Montana, North Dakota, New Jersey, New York, New Mexico, Nevada, Ohio, Oregon, Pennsylvania, South Carolina, South Dakota, Texas, Utah, Washington, Wisconsin. In the empirical analysis, I aggregate data by zip code and restrict the sample to zip codes that contain at least 100 house sales per year. The final sample used in the empirical analysis in Section 4 uses zip codes containing approximately 40 percent of the US population as at the 2000 Census.

I identify the ownership status of purchased properties in two stages.⁵ First, I infer owner-occupancy for each transaction by comparing the listed address of the buyer to the address listed for the property. I assume that owner occupiers are those whose address matches that of the property they purchased. Second, ZTRAX provides buyer description variable that reports whether they are an individual, a couple, a trust, a legal partnership, a company, a government entity, or some other kind of organization. Using this information, I restrict the sample of household owner-occupiers to those that are individuals or couples.⁶ I then classify non-owner occupiers as household or corporate investors. Household investors are coded as individuals or couples. Corporate investors are buyers listed as companies, partnerships, builders, developers, agents, contract owners, individuals doing business, or individual officers of organizations.⁷

⁴The conclusions drawn from the ZTRAX dataset are those of the researcher and do not reflect the views of Zillow. Zillow is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

⁵See Appendix A for details.

⁶Trusts and trustees are excluded. House purchases by these entities make up around one to two percent of all transactions.

⁷Government entities, non-profits, and religious organizations are excluded from this definition. Of these, only government purchases are significant, constituting around 0.5 percent of all transactions.

Table 1: Summary Statistics

	Pooled, 2001-2005			Pooled, 2006-2010		
	Owner Occupier	Household Investor	Corporate Investor	Owner Occupier	Household Investor	Corporate Investor
<i>A. Share of Total Purchases</i>	0.64	0.28	0.08	0.61	0.29	0.10
<i>B. Buyer Size:</i>						
Number of Properties: 1		0.65	0.14		0.65	0.15
Number of Properties: 2-5		0.24	0.19		0.22	0.20
Number of Properties: 6-25		0.07	0.22		0.07	0.21
Number of Properties: 26+		0.04	0.45		0.06	0.43
<i>C. Financing, Resales, Location:</i>						
Using a Mortgage	0.77	0.56	0.21	0.70	0.42	0.14
Resold Within 12 Months	0.06	0.12	0.35	0.04	0.10	0.32
Resold Within 24 Months	0.12	0.20	0.47	0.07	0.15	0.41
Out of Town		0.24	0.22		0.25	0.31
Observations	14,987,559			14,045,690		

Notes: .

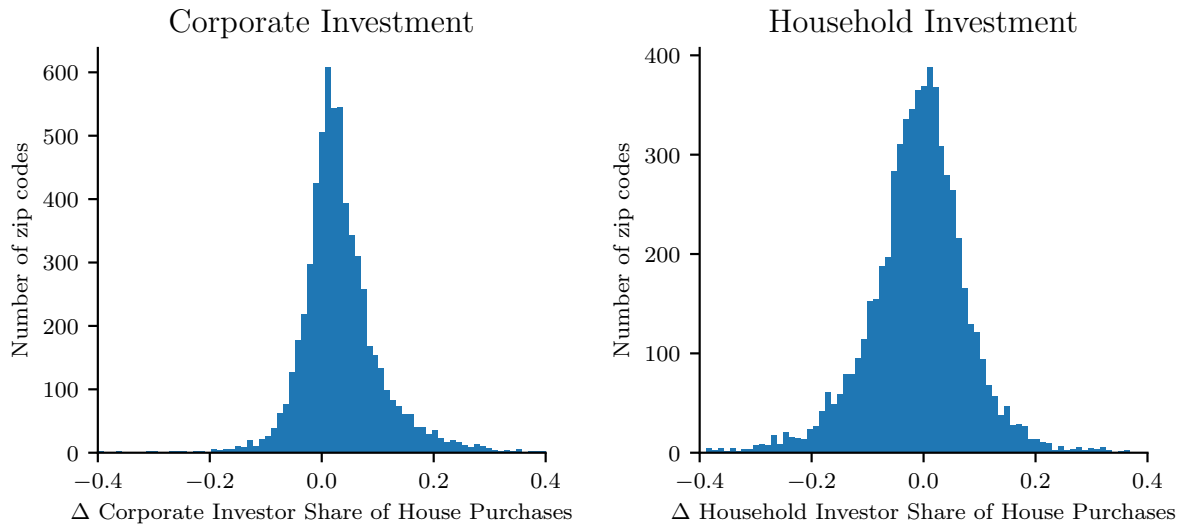
Sources: Author's calculations using ZTRAX.

Table 1 reports summary statistics across the three types of house buyer, pooled across all locations with available data, and split into the periods from 2001 to 2005 and 2006 to 2010. Panel A reports the share of total purchases associated with each buyer type. Nationally, the owner-occupier share of house purchases declined 3 percentage points between the housing boom and bust. This declining market share was absorbed by both household and corporate investors.

Panel B reports the proportion of purchases made by investors who bought a given number of properties within each 5 year period. These numbers are computed by tracking transactions across investors via their listed buying addresses.⁸ There are large differences between the size distribution of household and corporate investors. Household investment is heavily concentrated among investors purchasing just a single investment property. This is consistent with Haughwout et al. (2011), who show that in the 2000s around 70 percent of mortgage borrowing

⁸Note that this will overstate the number of properties purchased by an investor if they happen to change address and if the new occupant of that address also makes purchases in the sample period. I suspect this bias is small, and indeed the numbers reported here are comparable to those reported in Mills et al. (2019), who track individual investors by name rather than address.

Figure 1: Change in Investor Shares of House Purchases, 2006-2010



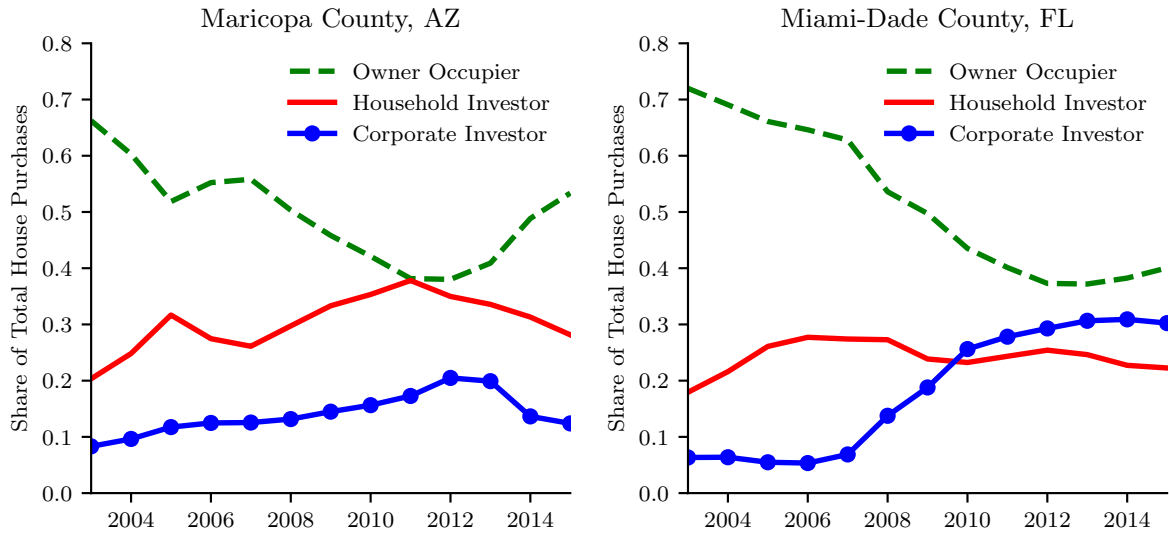
Source: Author's calculations using ZTRAX

associated with investors accrued to those with just two mortgages (i.e. one mortgage against a primary property and one against a secondary property). In contrast, corporate investment is skewed towards large investors: those purchasing more than 25 properties.

Panel C reports statistics summarizing financing, resales, and location of house buyers. The first row reports the fraction of each buyer type using a mortgage to finance their purchase. Owner occupiers are more likely to use mortgage financing than household investors, who in turn are more likely to use mortgages than corporate investors. From housing boom to housing bust mortgage financing dropped by 7 percentage points for both owner-occupiers and corporate investors, and by 14 percentage points for household investors. This reflects tightening mortgage credit conditions during this period. Unfortunately, the data does not report on non-mortgage sources of financing. For this reason it is not clear if, for example, corporate investors were affected by tighter non-mortgage credit due to the broader financial crisis during this period. The second and third rows of Panel C report the share of properties resold within 12 and 24 months. Owner occupiers are much less likely to resell their property within a short period of time than are household investors, who are in turn less likely to resell than corporate investors. These numbers are comparable to Mills et al. (2019), who report 12-month resale rates for owner-occupiers, household investors, and small corporate investors of 0.04, 0.17, and 0.45. The final row of Panel C reports the share of out-of-town buyers among household and corporate investors. I define an out-of-town purchase as one in which the buyer address is located in a different MSA to that of the property being purchased. During the housing boom, less than a quarter of all investment came from out-of-town buyers. However, in the housing bust the fraction of out-of-town corporate investors rose from 22 to 31 percent.

Figure 1 illustrates the significant variation in housing investment activity across housing markets during the housing bust. Each panel plots a histogram of the changes in investor shares

Figure 2: Housing Market Buyer Composition Through the Housing Bust



Source: Author's calculations using ZTRAX

of house purchases for zip codes between 2006 and 2010. For the median zip code, the corporate investor share rose 2.5 percentage points and the household investor share rose 0 percentage points. However, there are many more zip codes with declining household investor shares than there are zip codes with declining corporate investor shares. This reflects the fact that household investment, spurred on by cheap mortgage credit, had risen rapidly in many places during the housing boom (Haughwout et al., 2011; Mian et al., 2018). Variation in the investor shares is similar, with a standard deviation of 0.11 percentage points for both types of investors. Additionally, the correlation between changes in investor shares is slightly negatively correlated at -0.18. Finally, Figures B.1 and B.2 in the Appendix shows the geographic distribution of these changes in investment activity during the bust.

3.2. Mortgage Data

The program for the Home Mortgage Disclosure Act (HMDA) provides loan-level data about all US mortgage applications and originations. I restrict the analysis to all originated mortgages issued for the purpose of purchasing a house. I use information about the location of each mortgage origination to construct measures of total local mortgage activity. I use a Census tract-to-zipcode crosswalk file to aggregate mortgage originations to the zip code level. Note that total mortgage volumes may be affected by changes in house prices as homeowners borrow more against the value of their homes. To avoid this problem, I work with the number of mortgage originations. For every mortgage that is resold in the secondary mortgage market, the type of institution purchasing that mortgage is reported. I use this information to categorize mortgages as being sold to government sponsored enterprises (GSE), such as Fannie Mae or Freddie Mac, or to non-GSE institutions. I use both local and aggregate HMDA data from 1990

to 2016. Refer to Appendix A for more details.

3.3. Additional Data Sources

Zipcode-level house price indexes come from Zillow’s publicly available house price indexes.⁹ Annual income statistics by zip code are reported in the IRS Statistics of Income (SOI). Annual within-zip code employment and payroll statistics are in the County Business Patterns (CBP) survey. Local demographics and characteristics of the housing stock are from 2000 Decennial Census. All nominal variables are deflated by the CPI for all urban consumers from FRED. Refer to Appendix A for more details.

4. Empirical Analysis

In this section I present an empirical test of the investment stabilization channel of housing markets. Housing investment can act as a stabilizer if investment demand is less exposed to the shocks that affect homeowner demand. Moreover, the stabilization channel is stronger the more price elastic is investment demand to house prices. To provide intuition for these hypotheses, consider a simple model of housing market supply and demand. Suppose that the supply of houses sold in any given period is fixed, and the market features both homeowner and investor demand for houses. An equilibrium consists of the market clearing house price and the allocation of houses across homeowners and investors. Since supply is fixed, housing demands can be expressed as functions of the share of houses purchased by homeowners.¹⁰

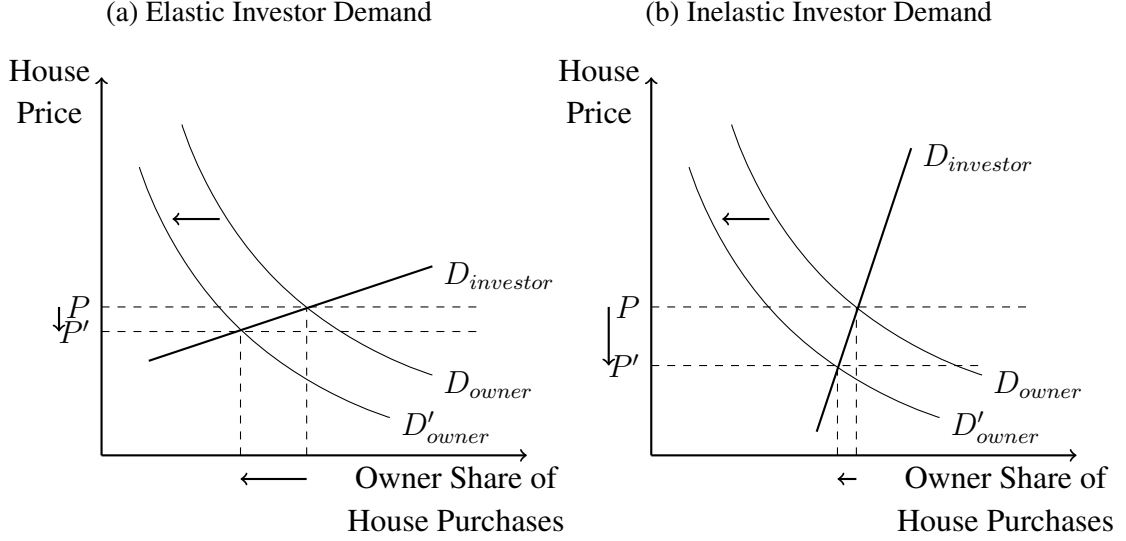
Figure 3 plots equilibrium housing market responses to a negative homeowner demand shock, where the two markets differ only by the elasticity of investor demand. If investors are not directly affected by the shock to homeowner demand, then the equilibrium decline in house prices is entirely determined by the elasticity of investment demand. Figure 3.a) shows that when investment demand is elastic, investors absorb a much larger fraction of the houses for sale and there is a very small decline in house prices. Figure 3.b) shows that when investment demand is inelastic, investors absorb a smaller fraction of houses purchased and prices decline by much more than in the elastic case.

In order to identify the investment stabilization channel, the empirical strategy exploits the relationship between housing demand shocks, changes in house prices, and changes in the composition of house purchases. I use exogenous changes in mortgage credit to model shocks to homeowner demand. I then estimate the relative change in house prices associated with changes in corporate and household investment activity. Since these estimated price responses are informative about the relative elasticities of investor demand, I use them as sufficient statistics for calibrating the structural macroeconomic model presented in Section 5.

⁹Although the ZTRAX data is a rich source of individual housing transactions, zip code, county, and city data have varying degrees of completeness, which presents difficulties in constructing broad and consistent house price indexes.

¹⁰Note that the inverse of the investor demand function is increasing in the owner share since it is decreasing in the investor share.

Figure 3: Housing Market Equilibrium with Homeowners and Investors



4.1. House Price Responses to Mortgage Credit and Housing Investment Activity

The empirical approach in this section predicts changes in house prices in response to mortgage credit shocks, conditional on changes in the composition of house purchases. I use zip code-level panel data from housing markets during the housing bust period of 2007 to 2010. Disaggregated, zip code-level data provides enough cross-sectional variation in the data to separately identify the heterogeneous effects of corporate and household investment on the responses of mortgage credit shocks. Finally, I use an instrumental variables regression strategy to identify the effects of changes in mortgage credit and to proxy for changes investor shares of house purchases. The second stage regression of the 2SLS specification is

$$\begin{aligned} \Delta \log P_{z,t} = & \alpha_{c,t} + \gamma \Delta \log P_{z,t-1} + \zeta \Gamma_{z,t} + \beta \Delta \log M_{z,t} \\ & + \delta_1 (\Delta \log M_{z,t} \times \Delta \text{Corporate Investor Share}_{z,t}) \\ & + \delta_2 (\Delta \log M_{z,t} \times \Delta \text{Household Investor Share}_{z,t}) + \varepsilon_{z,t} \end{aligned} \quad (1)$$

where the subscript z, t denotes a given zip code and year, $\Delta \log P_{z,t}$ is the annual growth rate of real house prices, $\Delta \log M_{z,t}$ is the growth rate of mortgage originations, and $\Delta \text{Corporate Investor Share}_{z,t}$ and $\Delta \text{Household Investor Share}_{z,t}$ are annual changes in the fraction of houses purchased by each type of investor. A county-by-year fixed effect $\alpha_{c,t}$ controls for county-specific trends in house price growth during the housing bust. I include the lag of the dependent variable $\Delta \log P_{z,t-1}$ in order to address possible serial correlation in house prices. And the vector $\Gamma_{z,t}$ includes additional controls for per-capita pre-tax income, the growth in employment by firms within the zip code, and growth in real annual payrolls of firms within the zip code.¹¹

¹¹Section 4.4 reports the results of a series of robustness checks including the addition controls for other plausibly confounding factors.

Note that Equation (1) uses changes in the number of mortgages originated $\Delta \log M_{z,t}$ rather than changes in mortgage volumes. This avoids a reverse causality problem associated with movements in house prices affecting the size of mortgages that borrowers choose to originate.

4.2. Instrumental Variables for Mortgage Credit and Housing Investment Activity

Changes in mortgage credit and investor purchase shares are likely to be endogenous to other determinants of local house prices. For example, a negative income shock decreases house prices, but is also associated with a decline in mortgage origination due to lower demand for houses. For this reason, I estimate Equation (1) via 2SLS using instrumental variables for mortgage credit and its interaction with the investor purchase shares. The first stage regressions of the 2SLS procedure are given by

$$X_{z,t} = \alpha_{c,t} + \gamma \Delta \log P_{z,t-1} + \zeta \Gamma_{z,t} + \sum_j \eta_j Z_{z,t}^j + v_{z,t}^i \quad (2)$$

where $X_{z,t}$ denotes one of the three explanatory variables in the second stage regression, Equation (1). The instrumental variables $Z_{z,t}^j$, indexed by j , enter each of the first stage regressions. The first instrument, discussed in more detail below, is the share of mortgages sold in the secondary mortgage market to non-GSE institutions between 1998 and 2000, denoted $\lambda_{z,98-00}^{nonGSE}$. The second and third instruments are the interactions between the non-GSE share and the lagged corporate investor share $\lambda_{z,98-00}^{nonGSE} \times \Delta \text{Corporate Investor Share}_{z,t-1}$ and the lagged household investor share $\lambda_{z,98-00}^{nonGSE} \times \Delta \text{Household Investor Share}_{z,t-1}$.

The instrument for mortgage origination growth measures local exposure to mortgage credit supply shocks, following Mian et al. (2009) and Mian et al. (2018). (Justiniano et al., 2017) show that beginning in 2003, non-GSE institutions experienced a rapid increase in both the volume of mortgage purchases and market share in the secondary mortgage market. This culminated in a near-collapse of non-GSE activity in 2008.¹² (Justiniano et al., 2017) argue that the rise and fall of non-GSE activity resembled a mortgage credit supply shock. This is because the timing of the increase in non-GSE activity was strongly associated with an increase in both mortgage originations and a decline in the mortgage interest rate spread over the risk-free rate. There was also geographic dispersion in the effects of this mortgage credit supply shock. Mian et al. (2009) show that locations with more exposure to non-GSE activity experienced more rapid growth in mortgage originations, more subprime mortgage borrowing, as well as higher mortgage default rates from 2005 to 2007. Mian et al. (2018) show that exposure to non-GSE activity predicted larger house price booms and busts, as well as more speculative investment activity during the boom.

¹²Drechsler et al. (2019) show that the market share of mortgages sold into private label securitization – those mortgages bought by non-GSEs and packaged into mortgage backed securities – began to slowly increase after 2012.

Both the growth in mortgage originations $\Delta \log M_{z,t}$ and the non-GSE share instrument $\lambda_{z,98-00}^{nonGSE}$ are constructed using HMDA data. First, I measure mortgage originations as all home purchase mortgages originated by one institution and sold to another institution within a reporting year. Then, following Mian et al. (2009), I compute the number of mortgages sold to non-GSE institutions. These institutions include: those purchasing explicitly for use in private securitization; commercial banks, savings banks, or savings associations; life insurance companies, credit unions, mortgage banks, or finance companies; purchases by affiliate institutions of the originator; and other types of purchaser.¹³ The non-GSE share is computed for the period 1998 to 2000 to ensure that local exposures to mortgage credit supply shocks are uncorrelated with contemporaneous developments in housing markets during the housing bust. I choose the 1998 to 2000 period because it occurs before the significant increase in non-GSE activity in the mid-2000s (Justiniano et al., 2017), but not so early that it is unlikely to predict subsequent developments in mortgage markets.

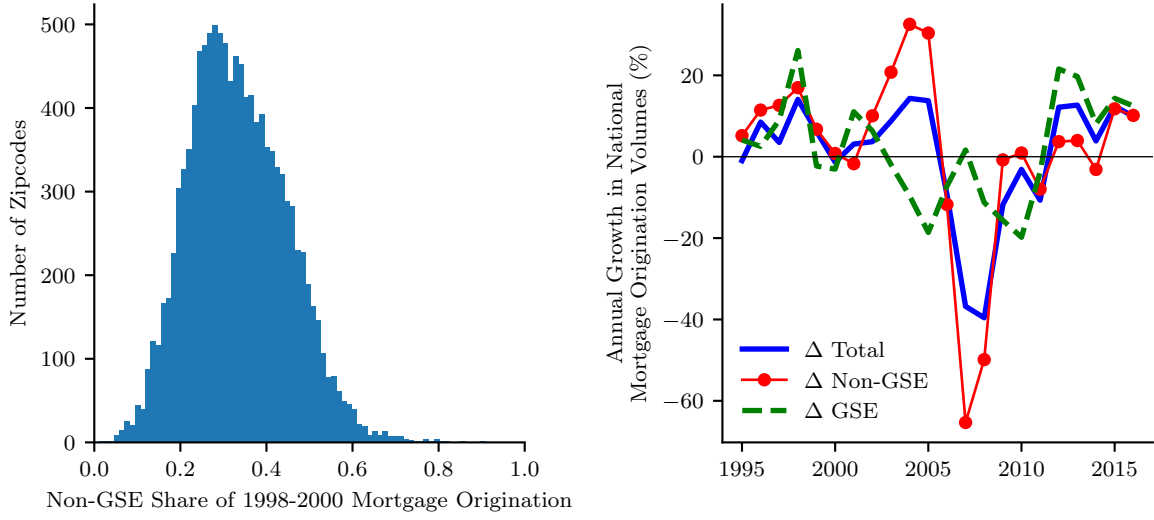
The left panel of Figure 4 plots the distribution of non-GSE shares. There is significant cross-sectional variation in the instrument, with a mean value of 0.33 and a standard deviation of 0.11. The right panel of Figure 4 plots the national growth rates of total mortgage originations, mortgages sold to non-GSE institutions, and mortgages sold to the GSEs (i.e. Fannie Mae and Freddie Mac). Non-GSE mortgage purchase activity was significantly more volatile than overall mortgage origination growth during the boom and bust. Notice, however, that the national pattern of non-GSE activity was very similar to overall activity prior to the housing boom. To understand the significance of the cross-sectional heterogeneity in mortgage credit supply shock exposure, note that from 2006 to 2007 mortgage origination in zip codes at the 10th and 90th percentiles of the non-GSE share distribution would have contracted by 13 and 32 percent, respectively, if total originations had followed the national decline in non-GSE mortgage activity.

The results of the first stage regressions from Equation (2) are reported in Table C.1 in the Appendix, and presented in binned scatter plots in Figure 5. Each panel in the figure shows the relevant instrument for each explanatory variable, where all variables are residualized relative to controls in the regression. The dashed red line shows estimated first stage relationship between instrument and explanatory variable, with estimates also reported in Table C.1. The instruments strongly predict changes in mortgage originations and its interactions with the corporate and household investor shares of house purchases.

Two recent papers have made some progress in providing instrumental variables for housing investment activity. First, Garcia (2019) studies the effect of investment during the housing boom using the local fraction of vacation properties as an instrument. However, this instrument is less useful for studying investment by corporations or households that are landlords. Second, Lambie-Hanson et al. (2019) study the effect of corporate investor activity using variation in exposure to a program instituted by Fannie Mae and Freddie Mac giving preference to homeowners seeking to buy foreclosed properties.

¹³See Appendix A for more details about the HMDA data. I also consider variations on this instrument in robustness exercises reported in Section 4.4.

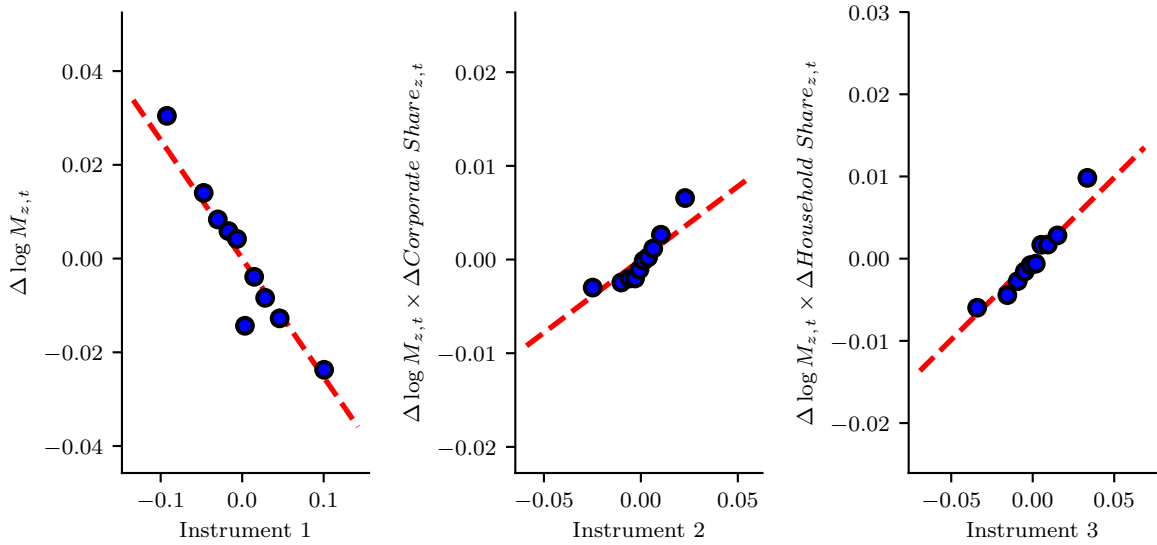
Figure 4: Local Mortgage Origination Shares and National Mortgage Origination Volumes



Notes: Total mortgage origination growth includes mortgages that were originated but not sold to the secondary market within a given year.

Source: Author's calculations using HMDA.

Figure 5: Effect of Mortgage Credit Instrument on Local Mortgage Origination Growth



Notes: Bin scatter plots of residualized explanatory variables and instruments, each representing a first stage regression in the 2SLS procedure. The residualized variables are reproduced from the fitted values from estimates of Equation (1). Each explanatory variable is plotted against the instrument that predicts it. These instruments are: instrument 1 = $\lambda_{z,98-00}^{nonGSE}$; instrument 2 = $\lambda_{z,98-00}^{nonGSE} \times \Delta Corporate Share_{z,t-1}$; instrument 3 = $\lambda_{z,98-00}^{nonGSE} \times \Delta Household Share_{z,t-1}$. The slopes of the red dashed lines report the first stage regression coefficients on the respective instruments.

Sources: Author's calculations using data from BLS, CBP, 2000 Census, FRED, HMDA, Zillow, ZTRAX.

4.3. Results

Table 2 reports the results of estimating Equation (1). All model specifications are estimated via 2SLS, using the instruments described in Section 4.2. Column (1) reports the average effect of changes in mortgage credit on local house price growth. I estimate an elasticity of 0.26, suggesting that a one standard deviation decrease in mortgage credit is associated with a 7.45 percent decline in house prices.

The estimated averaged effect of mortgage credit on house prices is consistent with previous estimates reported in the literature. Favara et al. (2015) produce estimates using changes in banking regulation as an instrument for the change in mortgage originations. With county-level data from 1994 to 2005, they estimate an elasticity of 0.14. Mian et al. (2018) also estimate the effect of mortgage credit on local house price growth. They report estimates for a reduced form specification, regressing differences in the local share of institutions with a high proportion of non-core liabilities on house price growth. Using zip code-level data from 2006 to 2010, they find that a one standard deviation greater exposure to high non-core liabilities lenders is associated with a 5 to 8 percent decline in house prices during this period.

Next I study how changes in investor activity are associated with the transmission of mortgage credit shocks to house prices. Columns (2) through (4) of Table 2 report the effect of the interaction between changes in mortgage credit and changes in the share of investor activity. Columns (2) and (3) include the interaction terms independently, while Column (4) jointly estimates the effects. The estimated coefficients for institutional investors are significantly more negative than for household investors. This is confirmed in the final rows of Column (5), which report a Wald test rejection of the null hypothesis of equality of the three interaction coefficients.

To interpret the negative value of the coefficients, note that a simultaneous decrease in mortgage credit and increase in the share of institutional investors, for example, is associated with an increase in house prices. Since the average effect of declining mortgage credit is negative, the increase in the share of institutional investors results in a smaller decrease in house prices than would otherwise be the case. That is, an increase in investor activity dampens the effect of a negative mortgage credit shock on house prices. To interpret the magnitude of the coefficients, note that taking both the average and the interaction effects into account, a simultaneous one standard deviation decrease in mortgage credit and one standard deviation increase in institutional investor activity is associated with a 5 percent decline in house prices. And a one standard deviation increase in household investor activity is associated with a 7 percent decline in house prices. These estimates suggest that while increasing investor activity is generally associated with dampened house prices movements, institutional investors have a much stronger dampening effect than do household investors. On impact, for a similar sized mortgage credit shock, locations with an increase in the share of institutional investor activity are associated with 29 percent smaller declines in house prices than locations with an increase in the share of household investor activity.

Table 2: Effect of Mortgage Credit and Investor Activity on Local House Prices

	$\Delta \log P_{z,t}$			
	(1)	(2)	(3)	(4)
$\Delta \log M_{z,t}$	0.260*** (0.053)	0.260*** (0.064)	0.266*** (0.053)	0.298*** (0.077)
$\Delta \log M_{z,t} \times$ $\Delta \text{Corporate Inv. Share}_{z,t}$		-2.147*** (0.530)		-2.599*** (0.665)
$\Delta \log M_{z,t} \times$ $\Delta \text{Household Inv. Share}_{z,t}$			-0.114 (0.243)	-0.716** (0.344)
Method	2SLS	2SLS	2SLS	2SLS
Sample	2007-2010	2007-2010	2007-2010	2007-2010
Observations	14,160	14,160	14,160	14,160
Zipcodes	3,960	3,960	3,960	3,960
Counties	470	470	470	470
Fixed Effects	County \times Year	County \times Year	County \times Year	County \times Year
Adjusted R-squared	0.44	0.39	0.43	0.27
F-statistics				
$F_{1 }$	22.16	28.06	33.65	34.88
$F_{2 }$	—	36.27	154.28	43.48
$F_{3 }$	—	—	—	75.56
Wald Statistic	—	—	—	13.85
p-value	—	—	—	0.00

Notes: All models estimated via 2SLS. The instrument for mortgage origination growth is local exposure to non-GSE mortgage purchases from 1998-2000. Changes in investor shares of house purchases are instrumented with their own lagged values. All models condition on: lagged house price growth; the contemporaneous shares of house purchases by each type of investor; the change in log-real per capita pre-tax zip code-level income; the change in log-employment by firms within the zip code; the change in log-real annual payroll by firms within the zip code. All models include county-by-year fixed effects. Column (1) reports the F-statistic for the first stage regression of the mortgage mortgage credit instrument on mortgage origination growth. Columns (2) through (4) report conditional F-statistics for the mortgage credit instrument and the instruments for the interactions between mortgage origination growth and the change in investor shares. Column (4) reports a Wald test for the hypothesis of equality between the coefficients on the interaction terms. Standard errors (reported in parentheses), F-statistics, and Wald test-statistics are clustered at the county level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Sources: Author's calculations using data from BLS, CBP, FRED, HMDA, IRS, Zillow, ZTRAX.

4.4. Robustness

To construct the instrument for mortgage origination growth, I follow Mian et al. (2009) in computing the share of non-GSE institution activity in the secondary mortgage market. However, it is not the case that every non-GSE institution packaged mortgages for PLS. For example, Figure B.4 in the Appendix shows that the HMDA-reported volume of mortgages originated for sale directly to PLS is less than a quarter of the volume sold to non-GSE institutions more broadly. It is worth noting, however, that the level of direct-to-PLS sales in HMDA appears to be significantly under-reported relative to more direct measures of PLS activity reported elsewhere (see, for example, Justiniano et al., 2017). Nevertheless, Table C.2 reports results using alternative definitions of the mortgage credit supply shock exposure instrument. Columns (1) and (4) report the benchmark results from Table 2; Columns (2) and (5) report results using the share of mortgages sold directly to PLS; and Columns (3) and (6) report results using the share of mortgages sold to PLS as well as non-banks.¹⁴ The mortgage credit instrument constructed using only PLS activity is much weaker than either of the other instruments. However, I continue to find that corporate investor activity is associated with much smaller house price declines in response to credit shocks than is household investor activity.

Table C.3 in the Appendix explores whether the results are sensitive to the inclusion of controls for other plausibly confounding factors. Column (2) controls for the size of the run-up in house prices between 2001 and 2006. Since exposure to mortgage credit supply shocks predicts the increase in house prices during the housing boom, it is possible that the subsequent fall in house prices is simply a function of the size of the boom rather than of tightening of mortgage credit during the bust. Column (3) controls for several measures of housing supply, including: county-level annual growth in the number of housing units permitted; the Saiz (2010) housing supply elasticity at the CBSA level interacted with year-dummies; and the fraction of houses built prior to 1990 and the fraction of houses with four or fewer rooms, both measured at the zip code level and interacted with year-dummies.¹⁵ Housing supply may affect the volatility of house prices, which could influence both financial institutions' willingness to supply loans to a location and investors willingness buy into that location. Column (4) includes controls for the structure of the local banking market in 2000, including: the fraction of deposits held by banks that have a within-state headquarters; the Herfindahl index for deposits held across branches; and the Herfindahl index for deposits held across institutions. The structure of the local banking market may affect mortgage credit supply, as discussed in Drechsler et al. (2019) and Favara et al. (2015). Finally, Column (5) includes controls for local demographic factors in 2000 including: median age; fraction of households with no more than high school education; and the fraction of owner-occupiers. Demographics may predict mortgage credit supply, as discussed in Albanesi et al. (2017), but may also predict the evolution of the housing market during the housing bust.

¹⁴Non-banks are unlikely to hold individual mortgages for the purpose of balance sheet management, and so are more likely to have purchased mortgages for the purpose of securitization. See Appendix A for details about the definition of non-banks in HMDA data.

¹⁵Graham (2018) shows that the local composition of house characteristics is a strong predictor of local house price growth during the 2000s housing boom and bust

Table C.3 shows little change in the estimates when conditioning on prior house price rises, local housing supply, and local banking competition. However, the inclusion of the demographic controls has some impact on the estimated coefficients. Although the changes are not statistically significantly different from the benchmark results, I find that the direct effect of mortgage credit is smaller, and the coefficients on the measures of investor activity are larger. Nevertheless, it is still the case that corporate investor activity is associated with smaller declines in house prices than household investor activity in response to credit shocks.

Table C.4 in the Appendix reports results using alternative data samples. Column (2) extends the sample period back to 2006 and through to 2012, which makes allowance for housing markets with slightly earlier or later turning points (see, for example, Ferreira et al., 2011). Column (3) increases the minimum number of house sales in a zip code in a year from 100 to 250. This restriction excludes smaller zip codes and those that had few house sales during the housing bust. Column (4) excludes the so-called Sand States, whose housing markets tended to have much larger fluctuations in house prices in the 2000s. I find little qualitative difference in results across these samples, although I find significantly more dampening of house prices associated with corporate investors in the large-zip codes sample. This is consistent with evidence presented in Mills et al. (2019) that large institutional investors were more active in large metropolitan areas during this period.

Finally, Table C.5 in the Appendix reports results using growth in the number of mortgage denials as the measure of mortgage credit, rather than growth in the number of mortgage originations. Again, the results of this exercise are quantitatively similar to those presented in the benchmark analysis.

5. Model

I build a macroeconomic model of the housing market in order to interpret the main empirical findings of the paper. Thus, I use the model mechanism to infer features of investor behavior that help explain the finding that corporate investment activity in the housing market results in significantly smaller house price fluctuations in response to a mortgage credit shock than household investment activity.

The model is an incomplete market, heterogeneous agent, overlapping generations model with general equilibrium rental and housing markets. Households can choose to be renters or homeowners who finance housing using long-term mortgage debt. In addition, households may choose to purchase investment properties from which they earn rental income. A deep-pocketed corporate investor also buys and sells investment properties...

I build a model to explore the interaction between owner-occupiers, investors, credit, and housing markets. In particular, I am interested in the effect of changing credit conditions on investor activity and equilibrium house prices. In order to do this, I build a heterogeneous agents life-cycle model that features significant heterogeneity in housing, investment, and mortgage debt holdings. This heterogeneity contributes to the endogenous choices about homeownership and investor activity.

5.1. Environment

Life-cycle

Households live for a finite number of periods with age indexed by $j \in [1, \dots, J]$. Households earn labor income throughout their working life, retire after age J_{ret} , and die with certainty at age J .

Preferences

Household preferences are defined over non-durable consumption c , housing services s , and end-of-life bequests of wealth w . Lifetime utility is given by

$$\mathbb{E} \left[\sum_{j=1}^J \beta^{j-1} u(c_j, s_j) + \beta^J v(w_{J+1}) \right]. \quad (3)$$

Period utility is given by

$$u(c, s) = \frac{(c^\chi s^{1-\chi})^{1-\sigma}}{1-\sigma}, \quad (4)$$

where χ is the share of consumption in non-housing services. Housing services are chosen each period by renting households, and are adjusted infrequently by home-owning households. The bequests function $v(\cdot)$ is defined over networth remaining at the end of life w_{J+1} . The function describes a warm-glow bequest motive following De Nardi (2004).¹⁶ Bequests are given by:

$$v(w) = \psi \frac{(w + \underline{w})^{1-\sigma}}{1-\sigma},$$

where w is the amount of the bequest, ψ is the strength of the bequest motive, and \underline{w} governs the luxuriousness of bequests.

Endowments

Households receive labor income during working-life, and a pension during their retirement. Labor income consists of a deterministic component, a persistent stochastic component, and a transitory stochastic component. During retirement households receive a fixed fraction of the deterministic and persistent components of income they received in the final period of working life. Log-income is

$$\log m_j = \begin{cases} g_j + y_j + z_j, & \text{for } j \leq J_{ret} \\ \log \omega + g_{J_{ret}} + y_{J_{ret}}, & \text{for } j > J_{ret}. \end{cases}$$

During working life, g_j follows a deterministic age profile during working life, y_j follows an AR(1) process, and z_j is an IID shock. The replacement rate of income during retirement is ω .

¹⁶Kaplan et al. (2017) also use warm-glow bequests to motivate wealth holding. In order to match observed levels of wealth inequality, Favilukis et al. (2017a) assume that only a fraction of households possess a bequest motive.

This arrangement proxies for dispersal from retirement accounts accumulated during working life. Conditioning on the final period of deterministic and persistent income is a tractable way of modeling the relationship between the size of retirement accounts and recent working-life income.

Liquid Assets

Households can save, but may not borrow, in a liquid asset a . The return on liquid assets r is fixed and determined in financial markets in the rest of the world. In the initial period of life households may receive bequests in the form of liquid assets.

Housing

Housing services may be acquired by renting or owning property. In addition, households may purchase property for the purposes of investment.

Rental services s are a continuous choice each period, subject to the restriction that $s \leq \bar{s}$, where P_r is the price paid per rental unit. Both owner-occupied and investment properties are chosen from a finite set of available properties \mathcal{H} . Houses are purchased at the per-unit price P_h . All property sales are subject to a transaction cost f_s levied proportional to the total value of property sold. These costs represent closing and moving costs associated with house sales. Households pay for routine maintenance to avoid depreciation at rate δ . The cost of depreciation is proportional to the market value of all properties.

Unlike owner-occupied properties, investment properties generate rental income. Investors receive the market rental rate P_r but must pay a per-period cost ϕ proportional to the size of the investment property. This cost represents any additional maintenance or management costs associated with renting property to non-owner occupying tenants.

Note that in the steady state equilibrium house prices and rents are constant. However, in response to shocks prices adjust along the transition path. As a result, properties may earn capital gains for both homeowners and household investors.

Mortgages

Households can finance property using mortgage debt. In order to economize on state variables, a single mortgage is secured against the combined value of owner-occupied and investment properties. Mortgages are long-term debt contracts during. During the mortgage term, a fixed payment is required in every period unless the mortgage is refinanced or properties are sold and the mortgage is repaid. For tractability and following the literature, mortgages are amortized over the remaining life of a household. In this way, mortgage duration approximates the 30-year mortgage contracts common in the US housing market.

Let b denote an outstanding mortgage balance and r_b the mortgage interest rate. An age j household has $J - j$ years remaining on the mortgage, which yields the following mortgage

payment in the current period:¹⁷

$$\pi_j(b, r_b) = \frac{r_b(1 + r_b)^{J+1-j}}{(1 + r_b)^{J+1-j} - 1} b.$$

For a household making a mortgage payment, the end-of-period mortgage balance reflects accumulated interest during the period less the mortgage payment: $b' = (1 + r_b)b - \pi(b, r_b)$. The mortgage interest rate is larger than the risk-free interest rate, $r_b > r$, reflecting un-modeled term premia and default risk. Households can repay a mortgage more quickly than the schedule given by the constant amortization formula, however this requires refinancing which is costly.

At origination, mortgages are subject to a maximum loan-to-value (LTV) ratio constraint, given by

$$b \leq \theta_b P_h(h' + i'),$$

where θ_b is the maximum LTV ratio, and $P_h(h' + i')$ is the combined value of owner-occupied and investment property.

Following Greenwald (2018), new mortgages are also subject to a payment-to-income (PTI) constraint. Since investors earn rental income from their investment properties, the PTI constraint includes both labor income and gross rental income:

$$\pi_j(b, r_b) \leq \theta_m (m_j + P_r i').$$

where θ_m is the maximum PTI ratio.

New mortgages require the payment of both fixed and proportional costs at origination. The fixed cost, F_b , is paid regardless of the size of mortgage, while the proportional cost f_b is levied on the amount of debt borrowed. The proportional cost reflects the discount points levied on new mortgages, while the fixed cost reflects other origination fees associated with new mortgages.

Household Decision Problems

Households enter a period with the state vector $\mathbf{s} = \{a, h, i, b, y\}$, where a is liquid assets, h is the owner-occupied house size, i is the investment property size, b is the outstanding mortgage balance, and y is the persistent component of labor income. A household chooses between renting (R), maintaining its housing portfolio while making any required mortgage payments (N), and adjusting its housing portfolio and mortgage debt (A). The discrete choice of a household at age j with state \mathbf{s} is

$$V_j(\mathbf{s}) = \max \{V_j^R(\mathbf{s}), V_j^N(\mathbf{s}), V_j^A(\mathbf{s})\},$$

where V_j^R is the value function of a renter, V_j^N is the value function of an owner that does not adjust, and V_j^A is the value function of an owner that adjusts its property portfolio.

¹⁷Note that the exponent term $J + 1 - j$ ensures that households make mortgage payments in every period of life, including the final period J . The final payment is $(1 + r_b)b$, which is the entirety of remaining principal plus interest. This ensures that networth is always non-negative at the end of life.

A renting household purchases housing services, consumes non-durable goods, and saves in liquid assets. If a house was previously owned, it is immediately sold and any outstanding mortgage is repaid from the proceeds. At the end of the period, renting households carry forward no housing assets or mortgage debt. The renter's problem at age j is

$$\begin{aligned} V_j^R(\mathbf{s}) &= \max_{c, a', s} u(c, s) + \beta \mathbb{E}(V_{j+1}(\mathbf{s}')) \\ \text{s.t. } & c + a' + P_r s + b(1 + r_b) = m_j + (1 + r)a + (1 - f_s)P_h(h + i) \\ & a' \geq 0, h' = 0, i' = 0, b' = 0 \end{aligned} \quad (5)$$

A non-adjusting household consumes non-durable goods, enjoys the housing services generated by the existing house, saves in liquid assets, pays housing maintenance costs, makes a mortgage payment on any outstanding mortgage debt, and receives rental income if it holds investment property. The problem of a non-adjusting household at age j is

$$\begin{aligned} V_j^N(\mathbf{s}) &= \max_{c, a'} u(c, h) + \beta \mathbb{E}(V_{j+1}(\mathbf{s}')) \\ \text{s.t. } & c + a' + \delta P_h(h + i) + \pi_j(b, r_b) = m_j + (1 + r)a + (P_r - \phi)i \\ & b' = b(1 + r_b) - \pi_j(b, r_b) \\ & a' \geq 0, h' = h, i' = i \end{aligned} \quad (6)$$

An adjusting household may consume non-durable goods, receive housing services generated by a newly purchased house, purchase new investment properties, sell any previously held properties, repay the entirety of any outstanding mortgage balance, originate a new mortgage, save in liquid assets, pay housing maintenance costs, and receive rental income on any new investment property. The problem of an adjusting household at age j is

$$\begin{aligned} V_j^A(\mathbf{s}) &= \max_{c, a', h', i', b'} u(c, h') + \beta \mathbb{E}(V_{j+1}(\mathbf{s}')) \\ \text{s.t. } & c + a' + \mathbb{1}_{h' \neq h} P_h(h' - (1 - f_s)h) + \mathbb{1}_{i' \neq i} P_h(i' - (1 - f_s)i) \\ & + \delta P_h(h' + i') + b(1 + r_b) = m_j + (1 + r)a + (1 - f_b)b' - \mathbb{1}_{b' > 0} F_b + (P_r - \phi)i' \\ & b' \leq \theta P_h(h' + i') \\ & \pi(b, r_b) \leq \theta_y (m_j + P_r i') \\ & a' \geq 0 \end{aligned} \quad (7)$$

Note that an adjusting household can refinance its mortgage by not adjusting its housing and investment properties: $h' = h, i' = i$. Finally, for tractability I assume households must own a primary property before purchasing an investment property.¹⁸

Corporate Rental Sector

An unconstrained risk neutral corporate investment firm is also active in the housing market. The firm trades property each period, rents out its housing stock, pays regular maintenance

¹⁸In the Survey of Consumer Finances, around 13% of household with residential investment property report not owning a primary property.

costs, and pays a convex portfolio holding cost associated with the number of houses held. The firm maximizes the present discounted value of profits via, where its problem is given by

$$\begin{aligned} p(I) = \max_{I'} \quad & P_r I' + P_h I - (1 + \delta) P_h I' - P_h Q(I') + \frac{1}{R} \mathbb{E} [p(I')] \\ \text{s.t.} \quad & Q(I') = \kappa^{-(1+1/\varepsilon)} \frac{I'^{1+1/\varepsilon}}{(1 + 1/\varepsilon)}. \end{aligned}$$

where $Q(\cdot)$ is the convex holding cost function. The first order condition yields

$$I' = \kappa^{1+\varepsilon} \left(\frac{P_r + \frac{1}{R} \mathbb{E} [P'_h] - (1 + \delta) P_h}{P_h} \right)^\varepsilon. \quad (8)$$

which is the corporate firm's investment demand curve. The demand curve is a function of the return to housing before holding costs, so increases in returns due to rising rents or temporarily declining house prices induce greater corporate housing investment. The parameter ε represents the elasticity of corporate investment demand. When $\varepsilon = \infty$, demand is perfectly elastic and the rental rate is pinned down by $P_r = (1 + \delta + 1/\kappa) P_h + \frac{1}{R} \mathbb{E} [P'_h]$. When $\varepsilon = 0$, corporate investment demand is perfectly inelastic and is given by $I' = \kappa$.

The corporate investment firm presented here is closely related to models of corporate rental investment described in the literature. In Chambers et al. (2009b) the firm produces rental units each period subject to a convex cost function. But while the corporate firm is active in rental markets it does not buy or sell property and so is not an active participant in housing markets. In Kaplan et al. (2017) the corporate firm's problem generates a Jorgensonian user-cost formula for the rental rates. This case is nested by the current formulation when the maintenance cost is paid in the period after use, the holding cost is not scaled by the price of housing, and $\varepsilon = \infty$.

Equilibrium

The solution of the model consists of a steady state, local general equilibrium in housing and rental markets. The households' state vector is $\mathbf{s} = \{a, h, i, b, y\} \in \mathcal{S}$. In what follows I drop the dependence of variables on the state vector. Let ι^X be an indicator function equal to one when a household makes the discrete choice $X \in \{R, N, A\}$. Let μ_j denote the measure of households aged j , defined on the state space \mathcal{S} . The total population across all cohorts is measure one: $\sum_{j=1}^J \mu_j = 1$. Let $Q_{j,j+1}$ denote a matrix describing the transition of the distribution of households across states \mathbf{s} and from age j to $j + 1$.

A *stationary recursive competitive equilibrium* is a set of value functions $\{V_j^R, V_j^N, V_j^A\}_{j=1}^J$, decision rules $\{\iota_j^R, \iota_j^N, \iota_j^A, c_j, a'_j, d_j, h'_j, i'_j, b'_j\}_{j=1}^J$, corporate rental demand I' , a house price P_h , a rental rate P_r , the supply of houses \bar{H} , and stationary measures $\{\mu_j\}_{j=1}^J$ such that:

- Given prices, households optimize and $\{V_j^R, V_j^N, V_j^A\}_{j=1}^J$ and $\{\iota_j^R, \iota_j^N, \iota_j^A, c_j, a'_j, d_j, h'_j, i'_j, b'_j\}_{j=1}^J$ are the value functions and decision rules associated with the solution to household Problems (5), (6), and (7),

- Given prices, corporate investment demand I' is given by the firm's first order condition, Equation (8).
- The rental rate P_r is consistent with rental market clearing:

$$\sum_{j=1}^J \left[\int \iota_j^D d_j d\mu_j \right] = \sum_{j=1}^J \left[\int (\iota_j^A + \iota_j^N) i'_j d\mu_j \right] + I'$$

where the expression on the left is household rental demand, and the expression on the right consists of the household and corporate investment properties supplied to the rental market.

- Given housing supply \bar{H} , the house price P_h is consistent with housing market clearing:

$$\sum_{j=1}^J \left[\int (\iota_j^A + \iota_j^N) h'_j d\mu_j \right] + \sum_{j=1}^J \left[\int (\iota_j^A + \iota_j^N) i'_j d\mu_j \right] + I = \bar{H}$$

where the expression on the left consists of the total number of owner-occupied houses held by households, and the total number of investment properties held by households and the corporate rental sector.

- The law of motion for the stationary distribution of households is

$$\mu_{j+1} = Q_{j,j+1} \mu_j$$

Details concerning the computational algorithm are discussed in Appendix D.

5.2. Steady State Calibration

I calibrate the model to capture salient features of US homeownership, investment ownership, and indebtedness in the mid 2000s, immediately prior to the housing bust. Panel A of Table 3 reports model parameters set according to external information. The model period is one year, households work for 41 periods (age 25 to 65) and die after 56 periods (age 80). The risk aversion parameter is set to 2, as is standard in the macroeconomics literature. The income process consists of the parameters for the deterministic age-profile, the persistent AR(1) component, and the transitory IID component of income. I follow a standard procedure for estimating the parameters of the deterministic and stochastic income processes using data from the Panel Study of Income Dynamics. The estimated persistence and volatility parameters are consistent with results reported in the literature (see e.g. Floden et al., 2001; Storesletten et al., 2004; Guvenen, 2009; Heathcote et al., 2014). Details of the estimation are reported in Appendix D. The replacement rate for retirement income is set at 50 percent of final period non-transitory income following Díaz et al. (2008).

The risk-free interest rate r is set to 1.5%, which matches the real rate on 10-year Treasury bills reported in FRED from 2003 to 2006. The mortgage interest rate r_b is set to 3.15%, which

Table 3: Model Parameters

Description	Parameter	Value	Source
A. Externally Calibrated Parameters			
Length of life (years)	J	56	Standard
Retirement age (years)	J_{ret}	41	Standard
Risk aversion	σ	2	Standard
Persistence of income shocks	ρ_y	0.948	PSID, own calculations
Std. dev. of persistent income shocks	σ_y	0.178	PSID, own calculations
Std. dev. of transitory income shocks	σ_z	0.294	PSID, own calculations
Retirement income replacement rate	ω	0.500	Díaz et al. (2008)
Risk free interest rate	r	0.0150	FRED
Mortgage interest rate	r_b	0.0315	FRED
Proportional mortgage origination cost	f_b	0.005	FRED
Proportional housing transaction cost	f_s	0.060	Standard
Housing depreciation rate	δ	0.030	Harding et al. (2007)
Maximum LTV ratio	θ_b	0.900	See text
Maximum PTI ratio	θ_m	0.400	See text
Elasticity of corporate demand	ε	0.000	See text
B. Internally Calibrated Parameters			
Discount factor	β	0.891	Calibrated
Non-durable share	χ	0.739	Calibrated
Bequest luxuriousness	\bar{w}	9.519	Calibrated
Bequest desirability	ψ	242.390	Calibrated
Minimum house size	\underline{h}	2.144	Calibrated
Fixed mortgage origination cost	F_b	0.026	Calibrated
Housing supply	\bar{H}	1.909	Calibrated
Landlord cost	ϕ	0.014	Calibrated
Corporate rental cost	κ	0.005	Calibrated

Notes:

corresponds to the real rate on 30-year mortgages over the same period. The proportional cost of originating a mortgage, f_b , is set at 0.5% of the size of the mortgage, consistent with the average size of mortgage origination fees and discount points in the mid 2000s. The proportional cost of selling a house, f_s , is set to 6%, in line with various estimates of property sales costs (see, e.g., Kaplan et al., 2017). The required maintenance (depreciation) rate for residential property δ is set to 3%, consistent with the estimates reported in Harding et al. (2007). In order to discipline the set of house sizes available for purchase, I make the strong simplifying assumption that only one house size (i.e. \underline{h}) is available for purchase as either owner-occupied

or investment property.¹⁹ I set the the maximum LTV and PTI ratios to 0.9 and 0.4, respectively. These values are consistent with the empirical evidence on the distribution of originated mortgages reported in Greenwald (2018).

To calibrate the size of bequests received by households at the beginning of life, I reproduce features of the observed distribution of networth for young households.²⁰ I use data for households aged 23 to 25 pooled across the SCF samples in 1998, 2001, 2004, and 2007. I split households into five income bins, and within each bin compute the fraction of households with positive networth. Within each bin, for households with positive networth I compute quantiles of the networth-to-income distribution. Liquid asset bequests are then allocated to households across the initial income distribution in the model according to the empirical distribution of networth-to-income.²¹

Finally, for the steady state calibration of the model I set the corporate elasticity ε to zero. All else equal the elasticity governs the response of corporate investment to changes in housing returns, which occur outside of the steady state. When $\varepsilon = 0$, I calibrate the corporate holding cost scale parameter κ to match the share of purchases made by corporate investors. As discussed in Section 5.3, a one-to-one mapping between ε and κ allows for experiments that keep the steady state constant while varying the elasticity of the corporate investor.

Panel B of Table 3 reports the model parameters calibrated via simulated method of moments (SMM). I use a SMM procedure that chooses the values of nine parameters $\{\beta, \chi, \bar{w}, \psi, \underline{h}, F_b, \phi, \kappa, \bar{H}\}$ to minimize the distance between a set of model moments and their empirical counterparts. I choose an over-identified SMM procedure because several of the parameters influence multiple model moments, and because many of the cross-sectional household statistics used as moments are correlated with each other. The discount factor β governs both household wealth accumulation and indebtedness. The weight on non-durable consumption in the utility function χ determines the share of housing services in consumption, which indirectly affects both homeownership rates and indebtedness. The bequest parameters ψ and \bar{w} affect savings behavior and wealth inequality as households approach the end of their lives. The minimum housing size \underline{h} is associated with the affordability of housing relative to renting, which influences the homeownership rate of the young, investment ownership rates, and the indebtedness of both homeowners and investors conditional on holding a mortgage. The landlord cost ϕ enters the steady state rental return for household investors and so affects both investment ownership rates and indebtedness conditional on being an investor. The fixed mortgage origination cost F_b affects the illiquidity of housing since it makes equity extraction more costly (for a discussion. Gorea et al., 2017, see). The investment firm's holding cost κ sets the level of corporate housing demand, which determines the share of house purchases made by the corporate sector. Finally, the supply of housing \bar{H} affects the average cost of all housing

¹⁹This is also a significant aid in computational tractability. In several unreported experiments, I verified that this assumption does not significantly affect the distribution of homeownership or indebtedness relative to, for example, making 2 or 3 house sizes available for purchase.

²⁰This is similar to the procedure adopted elsewhere in the literature, for example, Chambers et al. (2009b) and Kaplan et al. (2017).

²¹I opt for this relatively simple procedure to avoid the difficulty of distributing observed liquid assets, houses, investment properties, and mortgage debt to households in the model.

services, which primarily determines the overall homeownership rate.

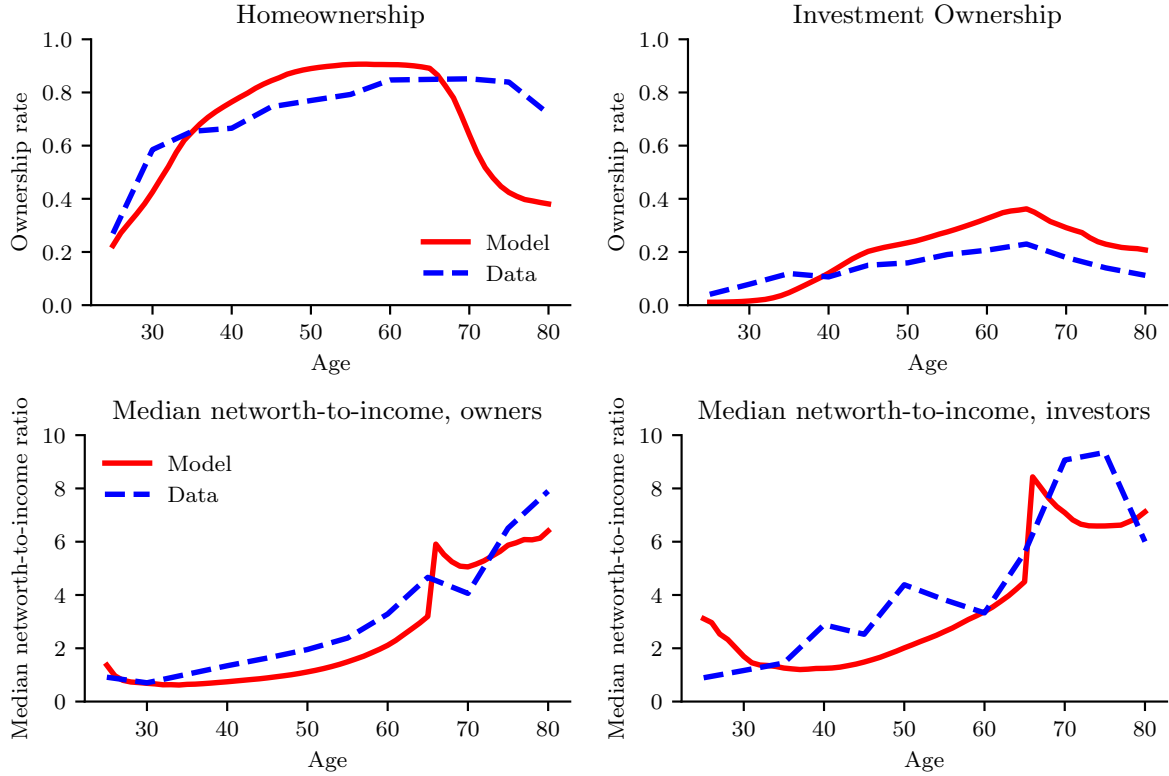
Table 4: Model Fit to Targeted and Non-Targeted Moments

Description	Model	Data	Source
A. Targeted Moments			
Homeownership rate	0.69	0.69	FRED, 2006
Investment ownership rate	0.20	0.15	SCF, 2007
Fraction of owners with mortgage	0.79	0.76	SCF, 2007
LTV ratio, owners with mortgage, p50	0.77	0.51	SCF, 2007
Mortgage debt/income, owners with mortgage, p50	1.98	1.53	SCF, 2007
Fraction of investors with mortgage	0.66	0.74	SCF, 2007
LTV ratio, investors with mortgage, p50	0.39	0.38	SCF, 2007
Mortgage debt/income, investors with mortgage, p50	1.55	1.52	SCF, 2007
House value/income, owners, p50	2.58	2.98	SCF, 2007
Networth/income, p50	0.98	1.18	SCF, 2007
Median networth ratio, ages 65-80 to 40-55	1.74	1.72	SCF, 2007
Homeownership rate, age ≥ 70	0.46	0.83	SCF, 2007
Homeownership rate, age ≤ 35	0.44	0.51	SCF, 2007
Annual mortgage refinancing rate	0.10	0.12	Bhutta et al. (2016)
Corporate investor share of purchases	0.08	0.07	ZTRAX, 2005-2007
B. Non-Targeted Moments			
Networth/income, p10	0.18	0.00	SCF, 2007
Networth/income, p90	5.25	7.66	SCF, 2007
Housing networth/networth, owners, p10	0.42	0.48	SCF, 2007
Housing networth/networth, owners, p50	0.76	0.95	SCF, 2007
Housing networth/networth, owners, p90	0.95	1.07	SCF, 2007
Investor share of total household-held housing	0.31	0.43	SCF, 2007
Household investor share of purchases	0.25	0.24	ZTRAX, 2005-2007
Annual fraction of houses sold	0.03	0.10	Ngai et al. (2019)
Household investor share of rental stock	0.99	0.88	Chambers et al. (2009a)
Corporate investor share of rental stock	0.01	0.12	Chambers et al. (2009a)

Notes: For consistency with the model, networth in the data is measured as total net housing wealth and net liquid assets. Following Kaplan et al., 2014, liquid assets are: checking, saving, money market and call accounts, plus directly held mutual funds, stocks, corporate bonds and government bonds. Liquid liabilities are: credit card balances.

Table 4 reports the fit between the model and data for the targeted moments and a range of non-targeted moments. The majority of these statistics are computed from the 2007 wave of the SCF. For consistency with the definition of networth in the model, I compute networth in

Figure 6: Household Ownership and Network Over the Life-Cycle

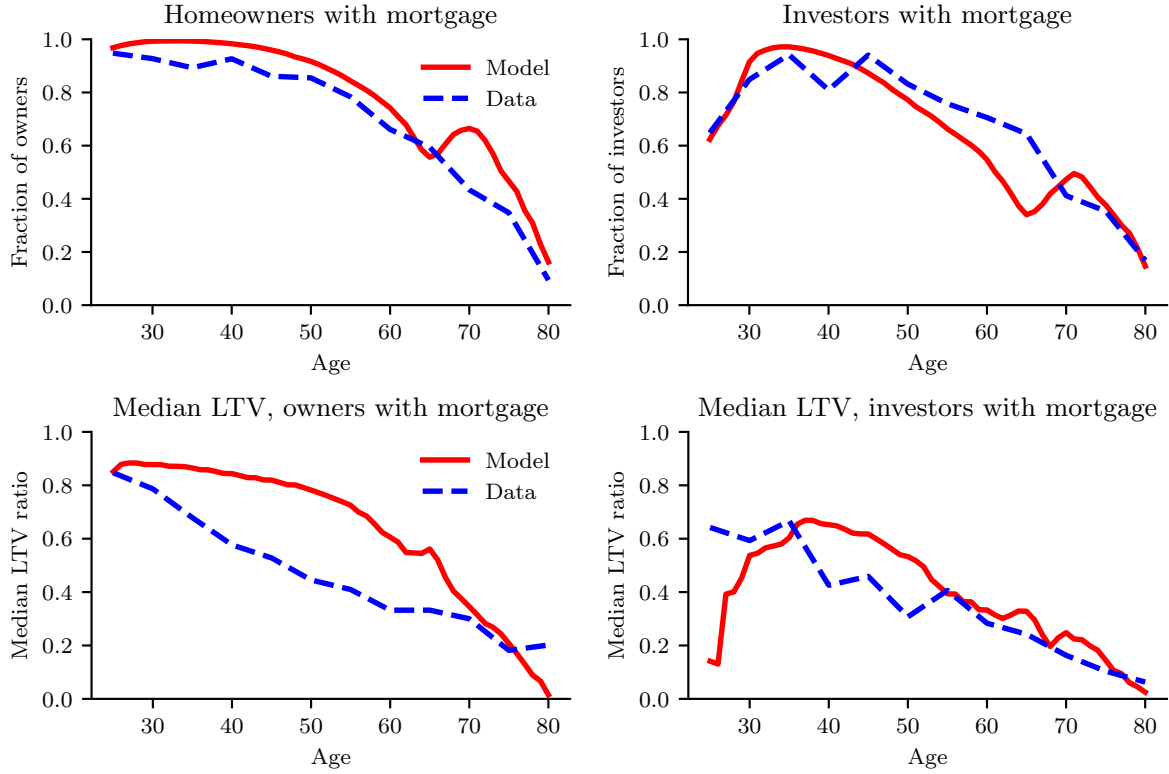


Notes: Data moments are computed from the SCF pooled across waves 1995, 1998, 2001, and 2004. The data moments are computed for centered, five-year windows around the ages 25 to 80 at five-year intervals. For consistency with the model, network consists of liquid assets and equity in primary and secondary property.

the SCF as owner-occupied and investor property less mortgage debt, plus liquid assets, and minus liquid liabilities. I measure investment ownership as the fraction of households that own secondary residential property. While 15 percent of households do so, only half as many report receiving rental income in the past year. Although all households with secondary property in the model are landlords, I opt to target the higher rate of secondary property ownership since I cannot distinguish between household motivations for purchasing property in the housing transactions data reported in Section 3. All mortgage holding rates, LTV ratios, debt-to-income ratios, and network statistics are computed using the combination of primary and secondary property mortgage debt. Data on mortgage refinancing is taken from Bhutta et al. (2016), who report an annual rate of 12 percent for 2007. The corporate and household investor shares of house purchases are computed as the median share across zip codes from 2005 to 2007.

Panel A of Table 4 shows that the model closely matches many of the targeted moments. The model somewhat overstates the rate of homeowner indebtedness. In the steady state, investment property only generates rental income. This keeps housing returns low relative to the substantial capital gains that are observed in the US (Jordà et al., 2019, see). The low returns in the model discourage investor borrowing, so the model increases overall household indebtedness in order to match the observed levels of investor debt. A related issue is that the

Figure 7: Household Indebtedness Over the Life-Cycle



Notes: Data moments are computed from the SCF pooled across waves 1995, 1998, 2001, and 2004. The data moments are computed for centered, five-year windows around the ages 25 to 80 at five-year intervals. For consistency with the model, mortgage holding rates and LTV ratios are computed for homeowners and investors with either primary property or secondary property mortgage debt.

model fails to match the homeownership rate of older households. A much stronger bequest motive would be required to match this homeownership rate, but this strengthens the wealth accumulation motive which again decreases both homeowner and investor levels of mortgage debt. Panel B of Table 4 reports the model fit relative to a set of non-targeted moments. The model does reasonably well at matching dispersion in the distributions of both network and homeowners' housing equity.

Figure 6 shows the evolution of ownership and networth for homeowners and investors over the life-cycle. I report these moments relative to comparable life-cycle moments computed for data from the 2007 wave of the SCF. Homeownership traces a similar hump-shaped life-cycle profile in both the model and data, although, as noted, the model fails to capture the higher homeownership rates at the end of life. Investment ownership in the model closely matches the low, tent-shaped profile observed in the data. In both cases, households begin to draw down on housing investment wealth as they enter retirement. Homeowner and investor wealth in the model, as measured by networth relative to income, rises over the life-cycle in line with the data. Additionally, the model captures the fact that household investors of all ages tend to be wealthier than homeowners and also accumulate wealth more quickly as they age. The

jump in networth-to-income at age 65 in the model is due to the sharp decline in income for all households at retirement. In contrast, households in the data retire at different ages which smooths through this sudden decline in income. Another discrepancy is that young household investors are much wealthier in the model than in the data. This is because investment in the model comes after households have purchased a home to live in. The only households in the model in a position to buy both primary and secondary property when young are those who received exceptionally large bequests relative to their income.

Figure 7 reports the life-cycle profiles of mortgage debt for owners and investors. The model matches the rate of mortgage holding for both homeowners and investors over time. However, the model significantly overstates the median LTV ratio of homeowners during middle age. The primary reason for this is that mortgages are amortized in the model at a much slower rate than in the data. In the model mortgages are repaid over households' entire lives, rather than the 30-year period that is typical of mortgage contracts held by households in the data. Additionally, given the constant amortization formula, households primarily repay mortgage interest during the early part of the mortgage contract and repay principal later in the contract.

5.3. Model Response to Mortgage Credit Shocks

I now use the model to study the role that investors play in stabilizing housing markets during the a mortgage credit contraction. To do this, the steady state of the model is perturbed by an exogenous, unexpected negative shock to mortgage credit supply. I can then compare equilibrium responses when each type of investor is the marginal house buyer by varying the elasticity of corporate investment demand. I first discuss the mortgage credit supply shock, and then explain the way in which I vary the marginal house buyer.

To model the mortgage credit supply shock, I exogenously change parameters in the model that capture the main features of the late 2000s mortgage crisis. This follows similar experiments conducted in the literature (for example, see Iacoviello et al., 2013; Hedlund, 2016; Guerrieri et al., 2017a; Kaplan et al., 2017; Favilukis et al., 2017a; Greenwald, 2018; Garriga et al., 2018; Garriga et al., 2019). The mortgage credit supply shock is represented by temporary exogenous changes, as summarized in Table 5. First, the mortgage interest rate r_m rises by 1 percentage point, which is the same size as the increase in the average mortgage interest rate spread over the ten-year treasury rate observed in the data.²² Second, the proportional mortgage origination cost f_b rises 0.25 percentage points, which is consistent with the increase in mortgage origination fees and discount points on 30-year mortgages observed in the data. Finally, both of the LTV and PTI constraints θ_b and θ_m decrease by 10 percentage points. This is consistent with evidence on changes borrowing behavior and constraints reported in Greenwald (2018). I assume that the economy begins in the steady state, is hit by a negative shock lasting seven years, and then transitions back to the original steady state. The choice of seven

²²This is also consistent with evidence in Justiniano et al. (2017), who estimate that the mortgage interest rate spread over the risk-free rate fell 80 basis points in response to the positive mortgage credit supply shock that drove the housing boom in the early 2000s.

years corresponds to the housing bust period between 2006 and 2012.

Table 5: Exogenous Negative Mortgage Credit Supply Shock

Description	Parameter	Boom Value	Bust Value
Mortgage interest rate	r_b	0.0315	0.0415
Proportional mortgage origination cost	f_b	0.0050	0.0075
Maximum LTV ratio	θ_b	0.90	0.80
Maximum PTI ratio	θ_m	0.40	0.30

Notes: Exogenous changes to parameter values for a negative mortgage credit supply shock. The shock is unexpected and switches the parameters from the boom state to the bust state for seven years, and then reverts to the boom state.

To explore the role of investors in the model, I compare the equilibrium responses of economies in which different investors are marginal house buyers during the mortgage credit contraction. I can exogenously control the marginal investor by varying the elasticity of corporate housing demand ε . When ε is close to zero, the corporate investor does not respond to changes in house prices or rents. In this case, as housing demand from homeowners falls, household investors must absorb the fall in demand and become the marginal buyers in the housing market. When ε is greater than zero, the corporate investor is sensitive to changes in returns and invests more in response to changes in prices and rents. For large enough values of ε the corporate investor becomes the marginal buyer following the shock, absorbing the entirety of the decline in homeowner demand for housing.

When comparing economies, they must differ only by the identity of the marginal investor at the time of the shock. To ensure that this is the case, I make use of a one-to-one mapping between the corporate investor cost parameter κ and the elasticity ε . For a given steady state equilibrium with prices P_h and P_r and equilibrium corporate investment demand I' , Equation (8) yields

$$\kappa = (I')^{\frac{1}{1+\varepsilon}} \left(\frac{P_r + \frac{1}{R}P_h - P_h(1+\delta)}{P_h} \right)^{\frac{-\varepsilon}{1+\varepsilon}}. \quad (9)$$

In this way, κ varies with ε , leaving the steady state of the economy unchanged.

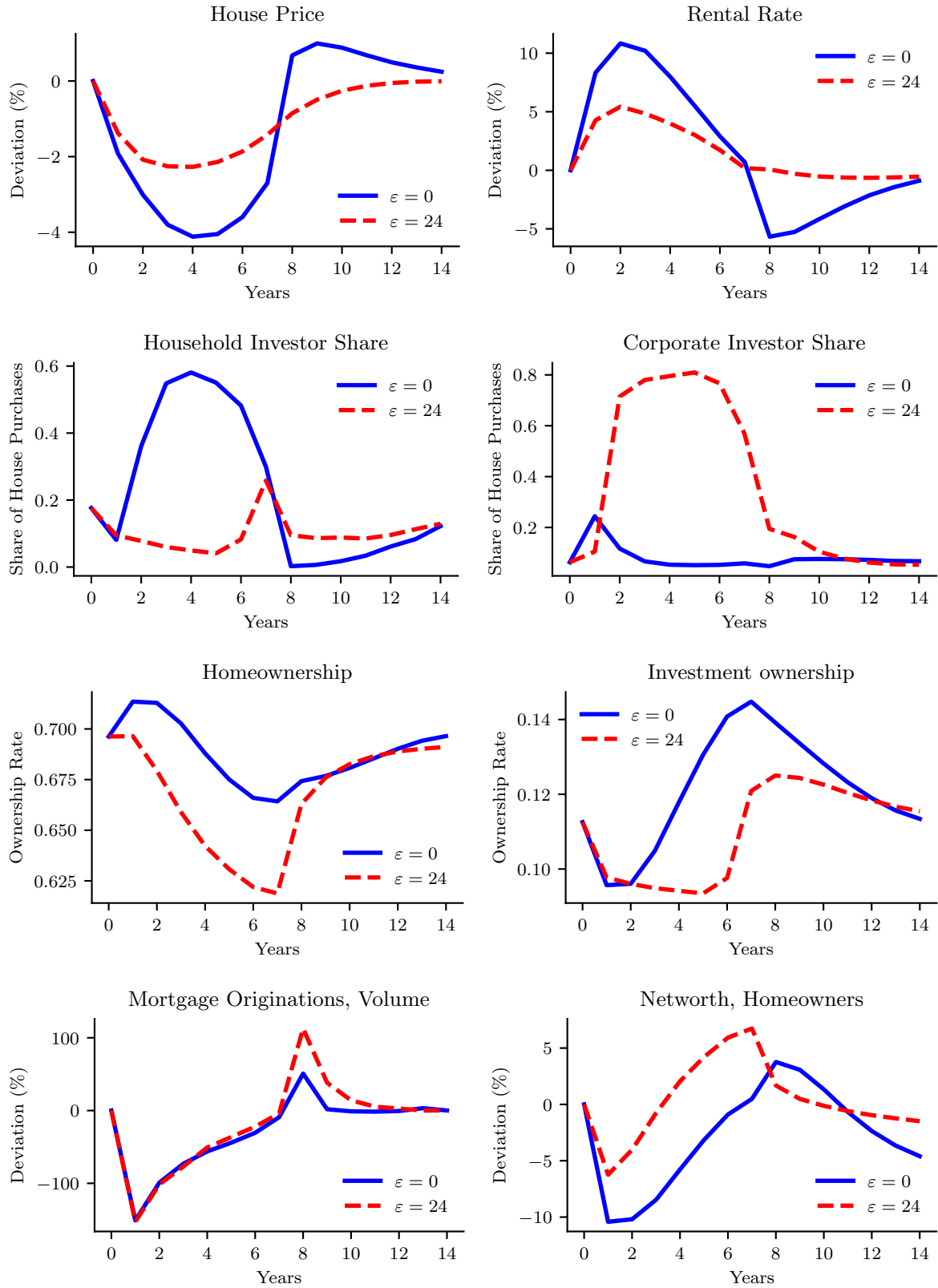
I compare economies that generate house price responses to the mortgage credit supply shock that closely correspond to the estimated relative price responses reported in Section 3. In the first economy, I normalize $\varepsilon = 0$. This represents housing markets that experienced significant increases in household investor demand but very little change in corporate investor demand. In the second economy, I choose ε so that the decline in house prices on impact is 30 percent smaller than in the economy with $\varepsilon = 0$. The relative decline in prices corresponds to the results reported in Section ?? for economies facing one standard deviation increases in the share of corporate and household investor purchases, respectively. To match this result, I set $\varepsilon = 24$.

Figure 8 presents the impulse responses to the negative mortgage credit supply shock. The mortgage credit supply shock makes mortgage origination more costly and tightens borrowing constraints, which results in a sharp decline in the volume of mortgages originated. The size of the decline in mortgage origination is similar in the two economies, suggesting similar declines in housing demand. However, the equilibrium response to this decrease in demand is markedly different. When ε is high, house prices are more stable than when $\varepsilon = 0$: on impact prices fall by 28 percent less, and from steady state to trough prices fall by 45 percent less.

The difference in the corporate elasticity of investment demand is reflected in the identity of the marginal house buyer during the course of the shock. When $\varepsilon = 0$, household investors absorb an increasing share of total house purchases, while the corporate purchase share is relatively flat. But when ε is high, corporate investors purchase an increasing share of houses, while the household investor share declines. These changes in the composition of the housing market are large enough to affect overall property ownership rates. When the corporate investor is the marginal house buyer, for example, it purchases such a large fraction of the housing stock that the homeownership rate declines by more than six percentage points, and investment ownership rates decline more than one percentage point. In contrast, when $\varepsilon = 0$, household investment initially declines and is associated with an initial increase in homeownership. However, as housing demand continues to decline, household investors purchase an increasing share of houses, which is associated with a decline in the homeownership rate and an increase in the investment ownership rate.

Changes in the marginal house buyer can be identified by the changing composition of house purchases. When the corporate investor is elastic, the share of total house purchases made by the corporate investor rises rapidly, while the share purchased by household investors falls. When the corporate investor is inelastic, the share purchases by the household investor rises, while the share purchased by the corporate investor is relatively flat. This pattern of purchases is reflected in the rate of household investment ownership. Investment ownership increases when the corporate firm is inelastic and decreases when the corporate firm is elastic.

Figure 8: Impulse Responses to a Negative Mortgage Credit Supply Shock



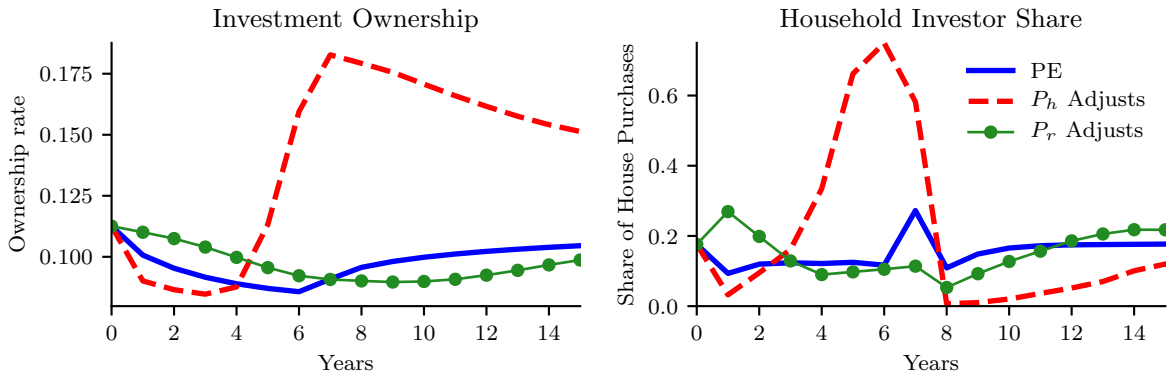
Notes: Impulse responses to a negative mortgage credit supply shock lasting seven years. Responses plotted for economies with $\varepsilon = 0$ and 24.

The Determinants of Household Investment in the Housing Bust

House prices decline by more when household investors are marginal house buyers because of the low elasticity of household investment demand. In this section I study the primary determinants of this elasticity. This includes household investment sensitivity to: mortgage credit; prices and rental rates; the liquidity of housing assets; and household wealth. Each of the following model experiments is conducted relative to the benchmark economy in which $\varepsilon = 0$.

First, consider the effect of the mortgage credit supply shock in partial equilibrium, when prices and rents do not adjust. In Figure 9, the solid blue lines show that household investment activity declines, as indicated by the decrease in investment ownership and the stable share of household purchases over the course of the shock. This contrasts with the general equilibrium responses in Figure 8, where investment ownership rates rise and household investors absorb a significant share of total house purchases. Table 6 reports the responses of different measures of house purchase activity in both the general and partial equilibrium. In partial equilibrium, investment activity – as measured by both investment purchases and ownership rates – falls well below steady state. In the fifth year of the shock, investment purchases remain 52 percent below steady state, and investment ownership rates remain 23 percent below steady state. Since the changes in mortgage credit are the only factors affecting the economy in partial equilibrium, these results suggest that household investment activity is extremely sensitive to declining credit conditions. For comparison note that in partial equilibrium home purchase activity falls by less than investment activity.

Figure 9: Household Investment in Partial Equilibrium



While household investors are less indebted than homeowners overall, as shown in Section 5.2, tighter mortgage credit raises the costs of investment. With no corresponding changes in house prices or rental rates, the return on housing investment falls, and households shift resources away from housing investment. When comparing partial equilibrium to general equilibrium in Table 6, I find that investment activity rises significantly. After five years, investment purchases are nearly 300 percent larger and investment ownership is 13 percent higher than in steady state. Note the contrast with home purchase activity: moving from partial to general equilibrium increases home purchases relative to steady state by less than 10 percentage points

Table 6: The Sensitivity of Property Purchases to a Mortgage Credit Supply Shock

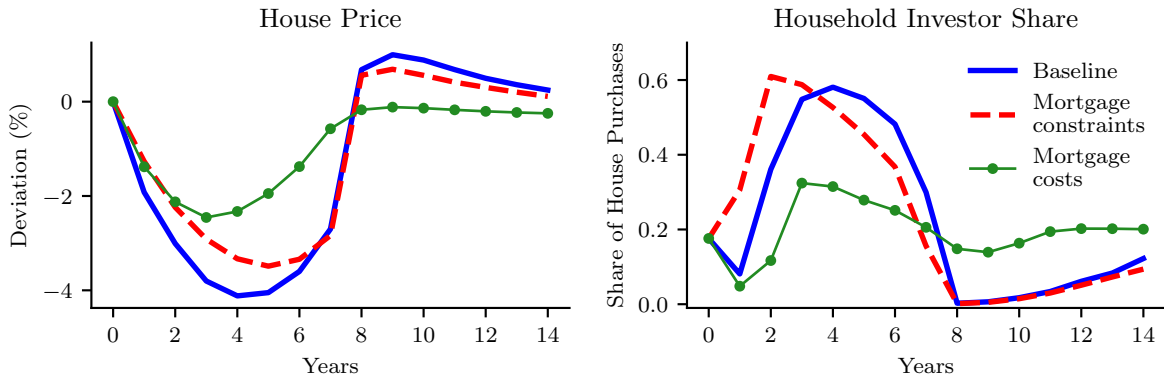
Year	Δ Investment Purchases (%)		Δ Investment Ownership (%)		Δ Home Purchases (%)		Δ Home Ownership (%)	
	<i>p.e.</i>	<i>g.e.</i>	<i>p.e.</i>	<i>g.e.</i>	<i>p.e.</i>	<i>g.e.</i>	<i>p.e.</i>	<i>g.e.</i>
1	-89.3	-83.9	-10.5	-14.2	-84.3	-76.3	-5.1	2.4
2	-77.8	-2.0	-15.3	-14.5	-70.5	-63.3	-9.2	2.2
3	-69.5	138.9	-18.6	-9.1	-58.2	-52.9	-12.5	1.1
4	-62.3	275.5	-21.0	1.9	-45.2	-43.8	-14.9	-0.9
5	-51.5	280.3	-22.7	13.0	-29.7	-36.5	-16.5	-2.8

Notes: Housing market activity in response to the mortgage credit supply shock under general equilibrium (*g.e.*) and partial equilibrium (*p.e.*). All variables measured as percent deviations from steady state.

after five years. In conjunction with the results in Figures 9 and 8, these results show that household investment activity is extremely sensitive to changes in house prices and rental rates.

I next consider partial equilibrium exercises in which only house prices or only rental rates adjust along the equilibrium path. The red dashed lines show responses when rental rates are held constant but house prices follow the path that occurs in general equilibrium. Here, after an initial fall, household investment rises rapidly in response to the decline in house prices. The green dotted line shows responses when prices are held constant, but rental rates follow their equilibrium path. In this case, household investment activity is largely unresponsive, closely tracking rates of investment under partial equilibrium. These results show that household investment is largely driven by changes in house prices. That is, household investment is largely motivated by capital gains rather than rental income. **CITATION!!!!!!**

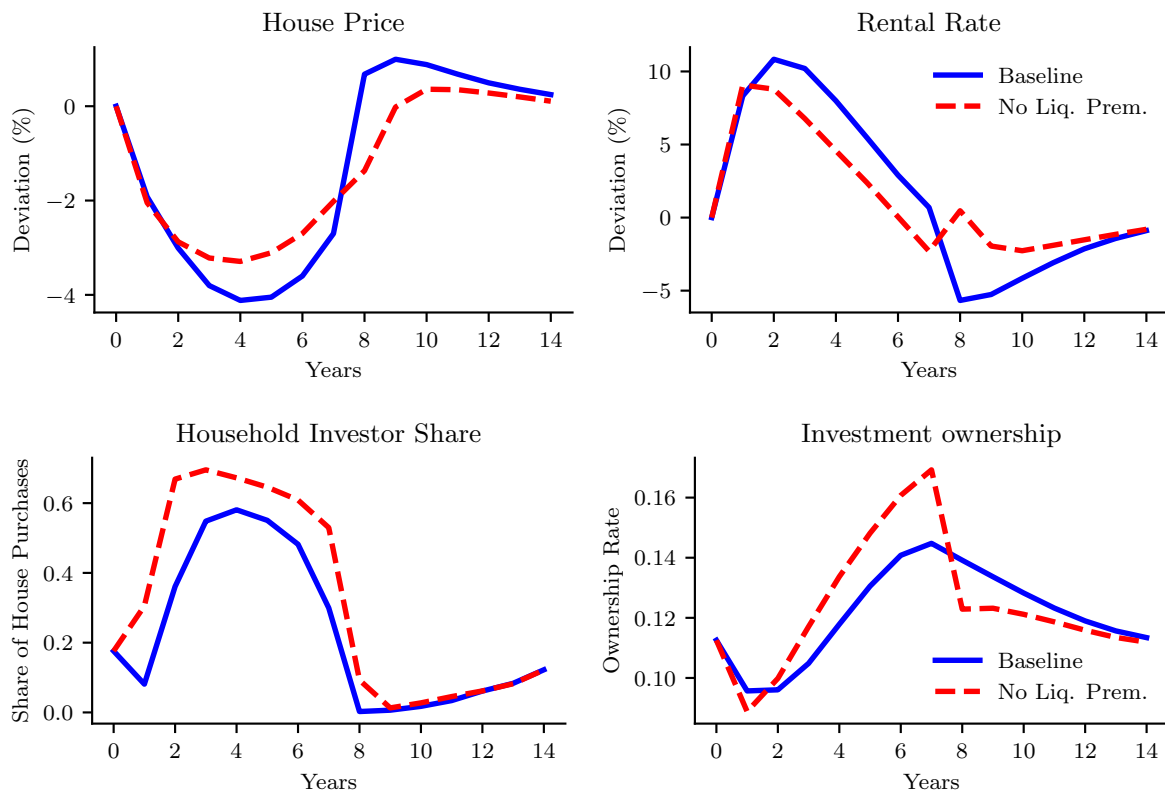
Figure 10: Impulse Responses to Components of the Mortgage Credit Supply Shock



Second, I study how different components of the mortgage credit supply shock affect household investment activity. Recall that the negative mortgage credit supply shock consists of increases in mortgage interest rates and origination costs, and decreases in the maximum LTV and

PTI constraints on mortgages at origination (see Table 5). Since the model features adjustable-rate mortgages, an increase in mortgage interest rates affects all existing borrowers. In contrast, tightening borrowing constraints only affects households originating new mortgages and only that subset of households that would have borrowed enough to be at or close to the constraints. Figure 10 compares equilibrium impulse responses for the baseline mortgage credit shock, a shock to mortgage borrowing constraints only (θ_b, θ_y), and a shock to mortgage costs only (r_b, f_b). Notice that household investment, as measured by the share of house purchases, rises on impact for the shock to borrowing constraints, but falls on impact for the shock to mortgage costs. Households that choose to invest are both wealthier and borrow with smaller LTV ratios than other homeowners (see Panel B of Table 4, and Figures 6 and 7). This means that potential household investors are further from the borrowing constraints when they tighten, and so are less exposed to that component of the mortgage credit shock than other households. In contrast, the shock to mortgage interest rates directly affects potential household investors since it reduces the returns to holding investment property while borrowing.

Figure 11: Impulse Responses With Lower Investment Property Transaction Costs



Notes: Impulse responses to a negative mortgage credit supply shock lasting seven years. Both sets of responses are for economies with $\varepsilon = 0$. The red dashed lines show responses for an economy in which the property transaction cost for investment properties f_s is set to zero for eight years.

Third, I consider the importance of the housing liquidity premium for household invest-

ment.²³ An important source of housing illiquidity is the transaction cost f_s associated with reselling a house. Although households can earn capital gains on housing by buying properties during housing bust and reselling during the recovery, transaction costs reduce the net return on holding investment property during this period. Therefore, the path of equilibrium house prices in response to the credit supply shock embeds a housing liquidity premium.²⁴ Since household investors are the marginal buyers of houses in the economy with $\varepsilon = 0$, part of the required return on housing along the transition path reflects the size of the liquidity premium for investors. I assess the importance of this liquidity premium by re-computing the impulse responses with lower housing transaction costs f_s . Specifically, I set $f_s = 0$ for investment properties for eight years. This is one year longer than the length of the credit supply shock, which enables investors to resell their properties during the house price recovery. Figure 11 shows that in comparison to the baseline economy, house prices fall by less, and household investment activity rises by more and more rapidly during the course of the shock. Temporarily lower investment transaction costs encourage household investors to purchase properties during the housing bust, but also encourage them to resell properties before costs rise again. This results in a sharp drop in investment ownership rates at the end of the housing bust. However, this is also when homeowner demand for houses rises, so the reallocation of properties from investors to homeowners prevents house prices from overshooting, as occurs in the baseline economy. By the house price trough in the fourth year, house prices fall by one fifth less in the model with lower investment transaction costs. This suggests that the liquidity premium on investment properties accounts for as much as 20 percent of the decline in house prices in economies where household investors are marginal house buyers.

6. Conclusion

In this paper I studied the stabilization role of investors in housing markets during the Great Housing Bust. I used transaction-level housing data to show that both corporate and household investors absorbed larger shares of the housing market as homeowner demand declined in the late 2000s. Using this data, the observed relationship between the change in the investor share of housing and the decline in house prices can be used to infer the elasticities of investor demands for housing. In the formal empirical analysis, I estimated heterogeneous house price responses to exogenous changes in mortgage credit given differences in corporate and household investor activity across housing markets. I showed that both types of investor activity are associated with dampened house price responses to mortgage credit. However, an increase in corporate investor activity is associated with a 30 percent smaller decline in house prices than an increase in household investor activity. This relative price decline suggests that corporate investment activity is much more elastic than household investor activity, meaning that corporate investment played a more effective stabilization role than household investment during the

²³Gorea et al. (2017) stress the importance of the illiquidity of owner-occupied property for explaining household consumption responses to income shocks.

²⁴Hedlund (2016) studies endogenous housing liquidity premia in a search and matching model of the housing market.

bust.

In the second half of the paper, I presented a structural macroeconomic model of the housing market to rationalize these differences in corporate and household behavior. Following the recent macro-housing literature, the core of the model features heterogeneous households that choose housing and mortgage financing in the face of uninsurable income risk. I build on that literature by introducing both household and corporate investors. The way in which these investors are modeled is motivated by micro-evidence showing that corporate investors are larger, trade housing more frequently, and rely much less on mortgage credit than do household investors. I calibrate the model to match the estimated relative decline in house prices associated with variations in the shares of corporate and household investors. In line with these estimates, I show that in response to an exogenous mortgage credit shock, house prices decline by much more when household investors are the marginal buyers of houses rather than corporate investors. I show that the much lower implied elasticity of household investment is due to the effect of changes in mortgage credit conditions, the illiquidity of housing assets, and changes in wealth due to the decline in the value of primary property. Following the mortgage credit shock, higher corporate investment activity is associated with more stable prices and rents, smaller fluctuations in networth and consumption, but larger declines in homeownership rates. In a final exercise I show that household welfare is higher when housing markets are more stable, despite the lower equilibrium rates of homeownership.

One limitation of the model is that the magnitude of equilibrium house price responses to mortgage credit shocks are too small. For example, when household investors are marginal house buyers the model only generates about 25 percent of the estimated total decline in house prices in response to a one standard deviation mortgage credit shock. This low volatility of house prices suggests that the elasticity of household investment demand is too high. Several extensions to the model could help to address this problem: property and capital gains taxes would reduce the returns to housing; idiosyncratic and aggregate house price risk would generate housing risk premia (see Landvoigt et al., 2015); and assets with higher returns such as stocks and equities would increase the opportunity cost of housing investment (see Favilukis et al., 2017a). I leave each of these extensions to future research.

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Appendices

A. Data

Data Sources

This section documents the sources of data used in the paper.

- Individual housing transaction data comes from Zillow’s Assessment and Transaction Database (ZTRAX). This data is proprietary, but is available from Zillow by request. For information regarding access, contact see <http://www.zillow.com/ztrax>.
- Zipcode house prices come from Zillow’s publicly available house price data at <http://www.zillow.com/data>.

- Zipcode income is from the IRS Statement of Income (SOI) statistics at <https://www.irs.gov/statistics/>.
- Zipcode demographic characteristics are from the 2000 Census, available at <https://factfinder.census.gov/>.
- Zipcode employment and county employment by industry is from the County Business Patterns data, available at <https://www.census.gov/programs-surveys/cbp/data/datasets.html>.
- Census tract-to-zipcode crosswalk files are retrieved from the Department of Housing and Urban Development at https://www.huduser.gov/portal/datasets/usps_crosswalk.html.
- County unemployment data is from the Bureau of Labor Statistics, available at <https://www.bls.gov/lau/data.htm>.

Zillow Transaction and Assessment Database

The full ZTRAX dataset contains more than 370 million public records from across the US for residential and commercial properties. Each transaction in ZTRAX contains information on the characteristics of a property and sale including transaction date, property type, sale type, buyer type, and so on.

The ZTRAX data is held in state-level files, each of which contains the entire set of assessment records and transactions for that state. The availability of information associated with each transaction varies by state, but also may vary across counties within states. Three states – Rhode Island, Tennessee, and Vermont – have various missing data in the ZTRAX database, and are excluded from the analysis entirely. For several other states, non-mandatory disclosure and outright prohibitions on the reporting of transactions prices mean that a very large proportion of transactions feature sales with prices reported as zero or missing.²⁵ For these states, property deeds and assessment records may still be reported to the ZTRAX database. I collect data on housing characteristics for these states, but I cannot use the transaction data on sales prices.²⁶ Instead, for these states I use publicly available, geographically aggregated Zillow house price indexes.

Identifying Ownership Status in ZTRAX

ZTRAX contains several variables describing ownership characteristics for house buyers. The two most important are a *Buyer Description* and *Occupancy Status*.

²⁵See <http://www.zillowgroup.com/news/chronicles-of-data-collection-ii-non-disclosure-states/> for more details.

²⁶The states with large numbers of missing transaction data are: Alaska, Idaho, Indiana, Kansas, Maine, Mississippi, Montana, New Mexico, Texas, Utah, and Wyoming

The buyer description variable indicates whether the buyer in a given transaction is an individual, a couple, a trust, a legal partnership, a company, a government entity, or some other kind of organization. The variable is populated in ZTRAX for virtually every transaction. I identify household owners as those buyers who are individuals, couples, and trusts. I identify institutional owners as those buyers who are legal partnerships, companies, government entities, or other organizations.

The occupancy status variable describes the stated or inferred occupancy status of the buyer of a property. Unfortunately, this variable is missing for a large number of transactions, is altogether unavailable for several states, and varies in quality over time and space within states. Instead of using the occupancy status variable, I identify occupancy from other information available in ZTRAX. ZTRAX provides a character string describing the street address of every property sold. Additionally, the street address of the buyer of a property is also provided. In many states over 90 percent of transactions are accompanied by a buyer address. I identify owner-occupiers as those whose listed buyer address exactly matches the address of the purchased property.²⁷

Finally, I identify household owner-occupiers as household owners from their buyer description information and who are owner-occupiers from their address information. I identify household property investors as household owners who are not owner-occupiers. And I identify institutional property investors as non-household owners.

Home Mortgage Disclosure Act Database

HMDA provides loan-level data on the universe of mortgage applications and originations in the US. A variety of information is reported about each loan. Location information about each loan is reported at the Census tract, county, MSA, and state levels. Zip code information is not provided, so I match Census tracts to zip codes using a tract-to-zip code crosswalk file provided by the Department of Housing. Because tracts may fall into more than one zip code, I use information on the share of tract residences in each zip code to weight each variable. To construct my measures of mortgage credit, I use the following variables associated with each loan in HMDA: Loan Purpose, Action Taken, Type of Purchaser, and Loan Amount.

Loan Purpose indicates whether a mortgage was used for a home purchase, home improvement, or refinancing. The main results only use home purchase mortgages.

Action Taken indicates whether the reporting institution originated a particular mortgage, denied an application for the mortgage, or purchased the mortgage from another institution. I only use mortgages that were originated by the reporting institution. Note that mortgages purchased by an institution need not have been originated in the reporting year. Additionally, these mortgages are likely to have been reported by originating institutions already, and so their inclusion would likely lead to double-counting.

Type of Purchaser indicates whether and to which institution a mortgage was sold. The

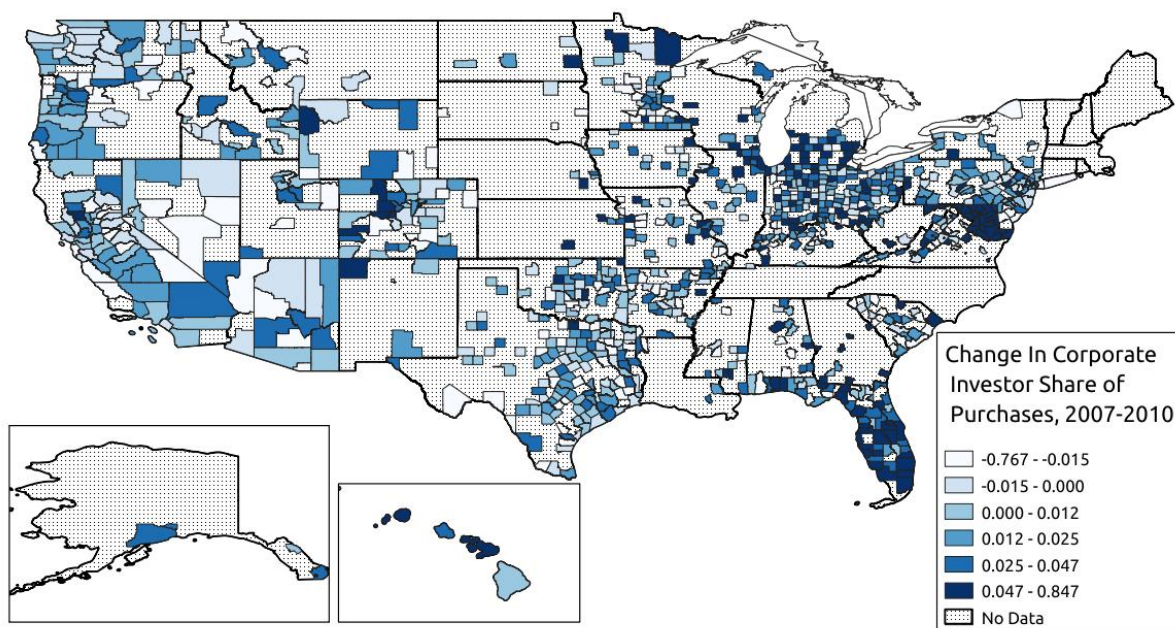
²⁷I also tried a fuzzy matching algorithm to compare addresses. Fuzzy matching enables identification of owner-occupiers when one of the listed addresses is mis-spelled. I found that this did not make a large difference to the number of identified owner-occupied properties.

first categorization includes mortgages that were not originated or were not sold within the year (HMDA code: 0). Conditional on having been originated, these are mortgages that the originator has chosen to keep on its balance sheet, at least for the time being. Note that nothing precludes the originator from selling this mortgage in the future. The remaining categories specify the type of institution that purchased the mortgage. The first four institutions are the GSEs: Fannie Mae, Ginnie Mae, Freddie Mac, and Farmer Mac (HMDA codes: 1,2,3,4). The remaining five categories cover non-GSEs: institutions purchasing explicitly for use in private securitization (HMDA code: 5); purchases by commercial banks, savings banks, or savings associations (HMDA code: 6); purchases by life insurance companies, credit unions, mortgage banks, or finance companies (HMDA code: 7); purchases by affiliate institutions of the originator (HMDA code: 8); and other types of purchaser (HMDA code: 9). This final category includes banks and thrift holding companies. See <https://www.ffiec.gov/hmda/faqreg.htm#purchaser>. Both Mian et al. (2009) and Mian et al. (2018) define non-GSE purchases as those associated with these final five categories of purchaser.

I use three measures of exposure to credit supply shocks. First, I use only mortgages sold explicitly into private label securitization (HMDA code: 5). Second, I use a broader measure that also includes mostly non-banks that are unlikely to hold mortgages for balance sheet management and so are likely to be purchasing mortgages for the purpose of securitization (HMDA codes: 5, 7, 9). Finally, I use the broad, non-GSE measure used in Mian et al. (2009) and Mian et al. (2018) (HMDA codes: 5, 6, 7, 8, 9).

B. Additional Figures

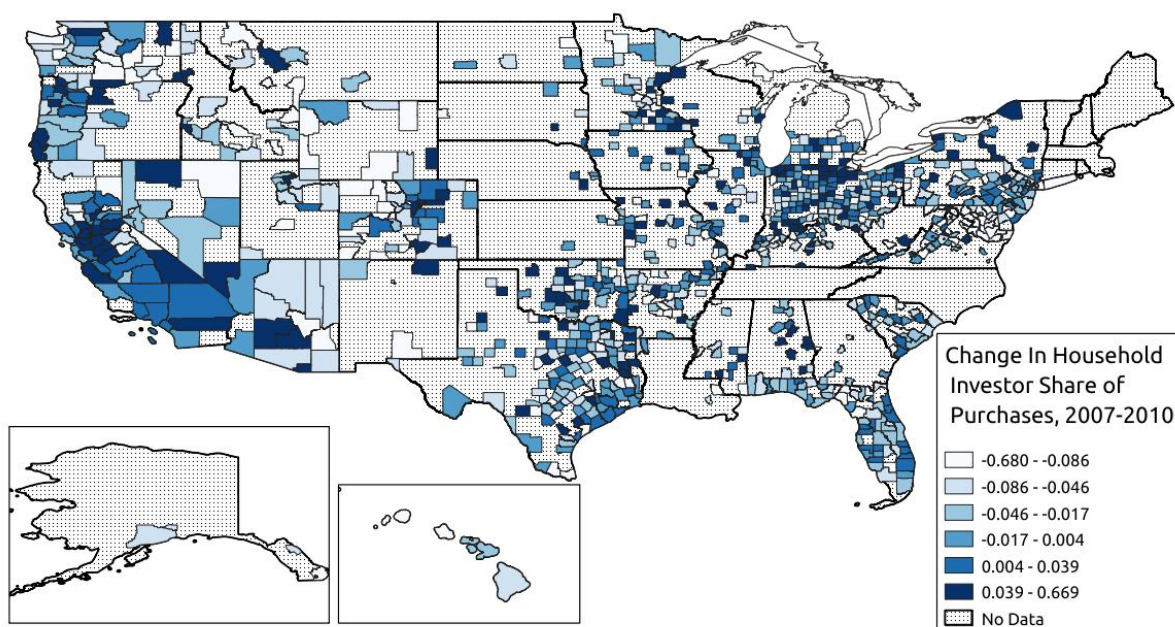
Figure B.1: Changes in Corporate Investor Share of Purchases Across Counties, 2006-2010



Source: Author's calculations using ZTRAX

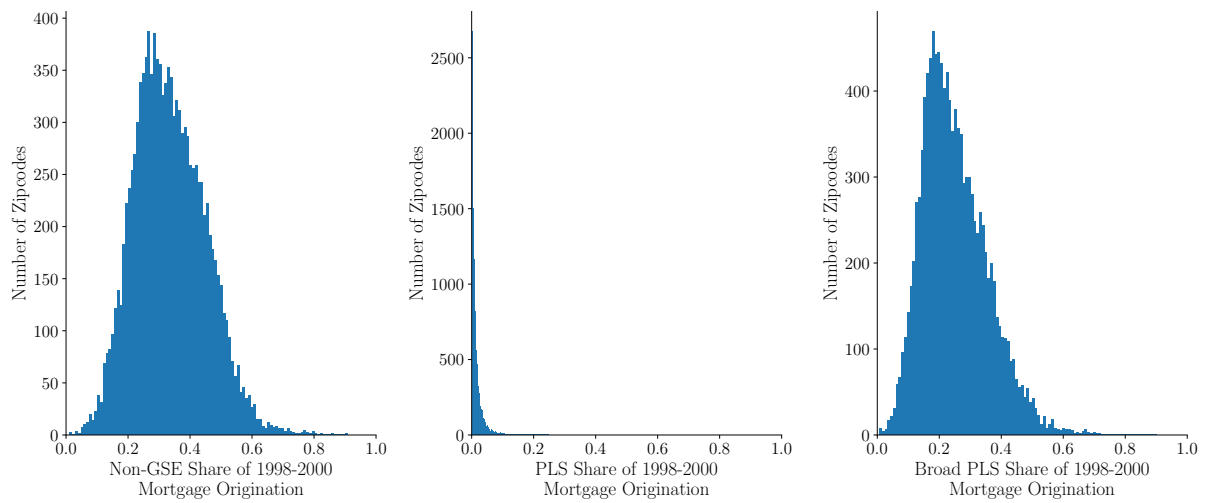
Figure B.2: Changes in Household Investor Share of Purchases Across Counties, 2006-2010

(a) Change in Household Investor Purchases



Source: Author's calculations using ZTRAX

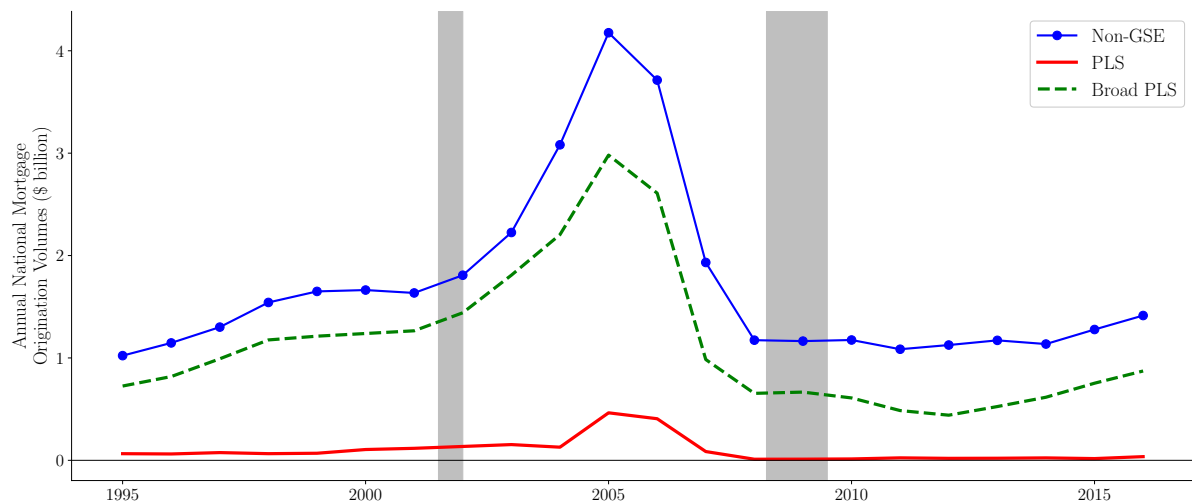
Figure B.3: Local Mortgage Origination Shares



Notes: Local mortgage origination shares by purchaser type between 1998 and 2000: non-GSE purchasers; direct-to-PLS purchasers; direct-to-PLS and non-bank purchasers.

Source: Author's calculations using HMDA.

Figure B.4: National Mortgage Origination Volumes



Notes: Annual national mortgage origination volumes by purchaser type.

Source: Author's calculations using HMDA.

C. Additional Tables

Table C.1: First Stage Regressions of the 2SLS Procedure

	(1)	(2)	(3)
$\lambda_{z,98-00}^{nonGSE}$	-0.253*** (0.052)	-0.003 (0.003)	-0.008 (0.005)
$\lambda_{z,98-00}^{nonGSE} \times$ $\Delta Corporate Investor Share_{z,t-1}$	0.904*** (0.236)	0.156*** (0.047)	0.056 (0.044)
$\lambda_{z,98-00}^{nonGSE} \times$ $\Delta Household Investor Share_{z,t-1}$	0.350*** (0.118)	0.025 (0.027)	0.197*** (0.029)
Sample	2007-2010	2007-2010	2007-2010
Observations	14,149	14,149	14,149
Zipcodes	3,960	3,960	3,960
Counties	470	470	470
Fixed Effects	County \times Year	County \times Year	County \times Year
F-statistic	23.59	11.04	45.07

Notes: First stage regressions for the 2SLS procedure following the specification in Equation (2). Column (1) reports the first stage regression for growth in mortgage originations. Column (2) reports the first stage regression for growth in mortgage originations interacted with the change in the corporate investor share of house purchases. Column (3) reports the first stage regression for growth in mortgage originations interacted with the change in the household investor share of house purchases. All models condition on: lagged house price growth; the contemporaneous shares of house purchases by each type of investor; the change in log-real per capita pre-tax zip code-level income; the change in log-employment by firms within the zip code; the change in log-real annual payroll by firms within the zip code. All models include county-by-year fixed effects. Each column reports the F-statistic for the instrument associated with the explanatory variable of that first stage regression. Standard errors (reported in parentheses) and F-statistics are clustered at the county level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Sources: Author's calculations using data from BLS, CBP, FRED, HMDA, IRS, Zillow, ZTRAX.

Table C.2: Effect of Mortgage Credit and Investor Activity on Local House Prices: Alternative Instruments

	$\Delta \log P_{z,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log M_{z,t}$	0.260*** (0.053)	0.282*** (0.081)	0.358*** (0.043)	0.298*** (0.077)	0.428* (0.223)	0.515*** (0.107)
$\Delta \log M_{z,t} \times$ $\Delta \text{Corporate Inv. Share}_{z,t}$				-2.599*** (0.665)	-3.938* (2.113)	-4.616*** (1.373)
$\Delta \log M_{z,t} \times$ $\Delta \text{Household Inv. Share}_{z,t}$				-0.716** (0.344)	-0.665 (0.493)	-1.000* (0.528)
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Mortgage Instrument	Non-GSE	PLS	Broad PLS	Non-GSE	PLS	Broad PLS
Sample	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010
Observations	14,160	14,160	14,160	14,160	14,160	14,160
Zipcodes	3,960	3,960	3,960	3,960	3,960	3,960
Counties	470	470	470	470	470	470
Fixed Effects	County \times Year	County \times Year	County \times Year	County \times Year	County \times Year	County \times Year
F-statistics						
$F_{1 }$	22.16	12.85	26.22	34.88	5.85	36.00
$F_{2 }$	—	—	—	43.48	5.33	37.00
$F_{3 }$	—	—	—	75.56	7.56	57.99
Wald Statistic	—	—	—	13.85	2.59	8.50
p-value	—	—	—	0.00	0.11	0.00

Notes: All models estimated via 2SLS. The instruments for mortgage origination growth consist of: local exposure to non-GSE mortgage purchases from 1998-2000 (Columns (1) and (2)); local exposure to mortgages sold directly into PLS from 1998-2000 (Columns (2) and (4)); local exposure to mortgages sold into PLS or to non-banks from 1998-2000 (Columns (3) and (6)). In all models, changes in investor shares of house purchases are instrumented with their own lagged values. All specifications include the same set of controls as in Table 2. All models include county-by-year fixed effects. Columns (1) to (3) report F-statistics for the first stage regression of the relevant mortgage mortgage credit instrument on mortgage origination growth. Columns (4) to (6) report conditional F-statistics for the mortgage credit instruments and the instruments for the interactions between mortgage origination growth and the change in investor shares. Columns (4) to (6) also report Wald tests for the hypothesis of equality between the coefficients on the interaction terms. Standard errors (reported in parentheses), F-statistics, and Wald test-statistics are clustered at the county level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Sources: Author's calculations using data from BLS, CBP, FRED, HMDA, IRS, Zillow, ZTRAX.

Table C.3: Effect of Mortgage Credit and Investor Activity on Local House Prices: Additional Controls

	$\Delta \log P_{z,t}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta \log M_{z,t}$	0.298*** (0.077)	0.306*** (0.069)	0.291*** (0.059)	0.262*** (0.073)	0.179** (0.090)
$\Delta \log M_{z,t} \times$ $\Delta \text{Corporate Inv. Share}_{z,t}$	-2.599*** (0.665)	-2.789*** (0.675)	-3.233** (1.266)	-2.353*** (0.586)	-1.709*** (0.476)
$\Delta \log M_{z,t} \times$ $\Delta \text{Household Inv. Share}_{z,t}$	-0.716** (0.344)	-0.869*** (0.314)	-0.232 (0.660)	-0.746** (0.361)	-0.457** (0.216)
Method	2SLS	2SLS	2SLS	2SLS	2SLS
Sample	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010
Additional Controls	Benchmark	$\Delta \log P_{z,01-06}$	Housing Supply	Bank Competition	Demographics
Observations	14,160	13,670	9,735	12,584	13,706
Zipcodes	3,960	3,960	3,960	3,960	3,960
Counties	470	470	470	470	470
Fixed Effects	County \times Year	County \times Year	County, Year	County \times Year	County \times Year
F-statistics					
$F_{1 }$	34.88	32.51	34.00	45.36	17.48
$F_{2 }$	43.48	38.92	25.30	55.10	27.85
$F_{3 }$	75.56	60.10	44.48	84.54	77.94
Wald Statistic	13.85	13.36	5.23	13.78	9.74
p-value	0.00	0.00	0.02	0.00	0.00

Notes: All models estimated via 2SLS. The instrument for mortgage origination growth is local exposure to non-GSE mortgage purchases from 1998-2000. Changes in investor shares of house purchases are instrumented with their own lagged values. All specifications include the same set of controls as in Table 2. Additionally, Column (2) controls for local house price growth between 2001 and 2006. Column (3) includes controls for local housing supply: the change in log-number of total housing units permitted at the county level; the Saiz (2010) housing supply elasticity at the MSA level interacted with year-dummies; the fraction of houses built prior to 1990 and the fraction of houses with four or fewer rooms, both measured at the zip code level and interacted with year-dummies. Because the supply elasticity is interacted with time and MSAs frequently overlap with counties, this specification include county and year fixed effects, rather than county-by-year fixed effects. Column (4) includes controls for the structure of the banking market measured in the year 2000 at the zip code level and interacted with year-dummies: the fraction of deposits held by banks that have a within-state headquarters; the Herfindahl index for deposits held across branches; the Herfindahl index for deposits held across institutions; Column (5) includes controls for local demographic factors measured in the year 2000 at the zip code level and interacted with year-dummies: median age; fraction of households with no more than high school education; the fraction of owner-occupier households. Each column reports conditional F-statistics for the mortgage credit instrument and the instruments for the interactions between mortgage origination growth and the change in investor shares. Additionally, Wald statistics report test results for the hypothesis of equality between the coefficients on the interaction terms. Standard errors (reported in parentheses), F-statistics, and Wald test-statistics are clustered at the county level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Sources: Author's calculations using data from BLS, BPS, CBP, Census, FDIC, HMDA, IRS, Zillow, ZTRAX.

Table C.4: Effect of Mortgage Credit and Investor Activity on Local House Prices: Alternative Samples

	$\Delta \log P_{z,t}$			
	(1)	(2)	(3)	(4)
$\Delta \log M_{z,t}$	0.298*** (0.077)	0.234** (0.107)	0.351*** (0.134)	0.182*** (0.065)
$\Delta \log M_{z,t} \times$ $\Delta Institutional\ Inv.\ Share_{z,t}$	-2.599*** (0.665)	-2.029 (1.459)	-5.035*** (1.641)	-1.115* (0.609)
$\Delta \log M_{z,t} \times$ $\Delta Household\ Inv.\ Share_{z,t}$	-0.716** (0.344)	-0.275 (0.369)	-1.054* (0.613)	-0.270 (0.385)
Method	2SLS	2SLS	2SLS	2SLS
Sample	Benchmark	2006–2012	$N_{sales,z,t} \geq 300$	No Sand States
Observations	14,160	24,953	8,268	6,673
Zipcodes	3,960	4,494	2,562	2,010
Counties	470	511	361	297
Fixed Effects	County \times Year	County \times Year	County \times Year	County \times Year
F-statistics				
$F_{1 }$	34.88	6.71	21.23	51.73
$F_{2 }$	43.48	5.95	21.84	29.64
$F_{3 }$	75.56	237.56	27.41	61.64
Wald Statistic	13.85	2.05	10.07	3.83
p-value	0.00	0.15	0.00	0.05

Notes: All models estimated via 2SLS. The instrument for mortgage origination growth is local exposure to non-GSE mortgage purchases from 1998-2000. Changes in investor shares of house purchases are instrumented with their own lagged values. All specifications include the same set of controls as in Table 2. Each column reports results using the same model specification, but with alternative data samples: Column (2) expands the sample period to 2006 through 2012; Column (3) includes only zip codes with at least 250 house sales in any given year; Column (4) excludes data from the “Sand States” and Florida (AZ, CA, CO, FL, NM, NV, TX, UT). Each column reports conditional F-statistics for the mortgage credit instrument and the instruments for the interactions between mortgage origination growth and the change in investor shares. Additionally, Wald statistics report test results for the hypothesis of equality between the coefficients on the interaction terms. Standard errors (reported in parentheses), F-statistics, and Wald test-statistics are clustered at the county level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Sources: Author’s calculations using data from BLS, BPS, CBP, Census, FDIC, HMDA, IRS, Zillow, ZTRAX.

Table C.5: Effect of Mortgage Denials and Investor Activity on Local House Prices

	$\Delta \log P_{z,t}$			
	(1)	(2)	(3)	(4)
$\Delta \log M_{z,t}$	0.217*** (0.059)	0.218*** (0.065)	0.217*** (0.056)	0.235*** (0.068)
$\Delta \log M_{z,t} \times$ $\Delta \text{Corporate Inv. Share}_{z,t}$		-1.249*** (0.364)		-1.445*** (0.450)
$\Delta \log M_{z,t} \times$ $\Delta \text{Household Inv. Share}_{z,t}$			-0.002 (0.170)	-0.327 (0.221)
Method	2SLS	2SLS	2SLS	2SLS
Sample	2007-2010	2007-2010	2007-2010	2007-2010
Observations	14,149	14,149	14,149	14,149
Zipcodes	3,960	3,960	3,960	3,960
Counties	470	470	470	470
Fixed Effects	County \times Year	County \times Year	County \times Year	County \times Year
F-statistics				
$F_{1 }$	23.10	25.90	29.62	27.40
$F_{2 }$	—	47.25	175.22	46.36
$F_{3 }$	—	—	—	140.28
Wald Statistic	—	—	—	10.24
p-value	—	—	—	0.00

Notes: All models estimated via 2SLS. The instrument for the growth in mortgage denials is local exposure to non-GSE mortgage purchases from 1998-2000. Changes in investor shares of house purchases are instrumented with their own lagged values. All specifications include the same set of controls as in Table 2. Column (1) reports the F-statistic for the first stage regression of the mortgage mortgage credit instrument on mortgage origination growth. Columns (2) through (4) report conditional F-statistics for the mortgage credit instrument and the instruments for the interactions between mortgage origination growth and the change in investor shares. Column (4) reports a Wald test for the hypothesis of equality between the coefficients on the interaction terms. Standard errors (reported in parentheses), F-statistics, and Wald test-statistics are clustered at the county level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Sources: Author's calculations using data from BLS, CBP, FRED, HMDA, IRS, Zillow, ZTRAX.

D. Additional Model Details

Income Process

During their working life, household income is constituted by deterministic and stochastic components. The deterministic component of income follows a hump-shaped life-cycle profile. The stochastic component of income follows a standard composite of persistent and transitory elements. The persistent component of log-income follows an AR(1) process, and the transitory component is an IID shock. Thus, log-income at any age j is given by

$$\log m_j = \log g_j + \log y_j + \log z_j$$

where g_j is the deterministic life-cycle component, y_j is an AR(1) process following $\log y_j = \rho \log y_{j-1} + \varepsilon_j$ with $\varepsilon_j \sim \mathcal{N}(0, \sigma_y^2)$, and z_j is an IID shock where $\log z_j \sim \mathcal{N}(0, \sigma_z^2)$. To calibrate this income process, I follow a standard minimum-distance estimation procedure from the literature (see Floden et al. (2001), Storesletten et al. (2004), Guvenen (2009), and Heathcote et al. (2014)).

I gather data on individual earnings from the Individual Data File from the 1999 to 2007 waves of the PSID. I filter observations according to the following criteria. I keep male household heads between the ages of 25 and 65 who were respondents in a given panel year. I drop observations for individuals who were retired, permanently disabled, home-makers, and students. I keep only individuals who were in families (or their split-offs) that were in the 1968 core sample, which was constructed as a representative cross-sectional sample of the population. I drop observations with missing information on age, education, and labor income, or for which labor income is non-positive. To measure earnings I use the annual earnings variable. Note that income is reported for the 2 years prior to the sampling date. For example, income reported in 1999 is actually annual earnings from 1997. I deflate this earnings measure using annual CPI from the associated reporting year (i.e. not the sample year). To remove the influence of outliers on my estimates, I remove observations in the top and bottom one percent of real earnings. Finally, the filtering procedure yields 2150 individuals with a total of 6930 observations across the sample period.

First, I estimate the life-cycle profile g_j by regressing log-earnings on a cubic polynomial in age, conditional on sample year dummies, and dummies for the number of years of education. This yields the polynomial coefficients: $\{\beta_{age}, \beta_{age^2}, \beta_{age^3}\} = \{0.27007, -0.00484, 0.00028\}$. Second, I take the residuals from the previous regression and compute several cross-sectional statistics to provide moment conditions for the GMM estimation. Specifically, I compute the cross-sectional variance of log-income, as well as the two-, four-, and six-year auto-covariances of log-income. These moments are reported in Table D.6.

The model for the income process generates the following variance and auto-covariance statistics:

$$\text{var}(\log m_j) = \frac{\sigma_y^2}{1 - \rho^2} + \sigma_z^2, \quad \text{cov}(\log m_j, \log m_j + n) = \rho^n \frac{\sigma_y^2}{1 - \rho^2}$$

Table D.6: Cross-sectional moments of individual earnings in the PSID

Variance	2-Year Auto-cov	4-Year Auto-cov.	6-Year Auto-cov
0.3977	0.2808	0.2483	0.2273

Notes: Cross-sectional moments computed using the residuals from a regression of log-income on a polynomial in age and dummies for sample year and years of education.

Source: Author's calculations using data from PSID waves 1999-2007.

Thus, the structure of auto-covariances in the data help to disentangle the relative volatility of the persistent and transitory components of income. I estimate the parameters $\{\rho, \sigma_y, \sigma_z\}$ by minimizing the difference between the set of moments generated by the model and the moments in the data. This yields $\{\rho, \sigma_y, \sigma_z\} = \{0.9479, 0.1777, 0.2942\}$. These estimates are very similar to those used elsewhere in the literature.

Computational Details

For computational convenience, I solve the model using a slightly modified set of state variables. The state space used in computations consists of cash on hand, primary property, secondary property, the current mortgage loan to value ratio, and the persistent component of income. In notation, $\mathbf{s} = [x, h, i, q, y]$, where $x = aR + m_j$ and $q = \frac{b}{P(h+i)}$. For this formulation, an adjusting household's problem becomes:

$$\begin{aligned}
 V_j^A(\mathbf{s}) &= \max_{c, a', h', i', q'} u(c, h') + \beta \mathbb{E}(V_{j+1}(\mathbf{s}')) \\
 \text{s.t. } & c + a' + P_h(\mathbb{1}_{h' \neq h} h' + \mathbb{1}_{i' \neq i} i') + \delta P_h(h' + i') + bR_b \\
 &= x + (1 - f_s)P_h(\mathbb{1}_{h' \neq h} h + \mathbb{1}_{i' \neq i} i) + (1 - f_b)b' - \mathbb{1}_{b' > 0} F_b + (P_r - f_i)i' \\
 & q' \leq \theta \\
 & q' \leq \frac{\theta_y m_j}{P_h(h' + i')\pi(1, r_b)} \\
 & b \equiv qP_h(h + i), \quad b' \equiv q'P_h(h' + i')
 \end{aligned}$$

Notice that the household chooses the mortgage loan-to-value ratio directly. A non-adjusting household's problem becomes:

$$\begin{aligned}
 V_j^N(\mathbf{s}) &= \max_{c, a'} u(c, h) + \beta \mathbb{E}(V_{j+1}(\mathbf{s}')) \\
 \text{s.t. } & c + a' + \delta_h P_h(h + i) + \pi(b, r_b) = x + (P_r - f_i)i \\
 & q' = q(R_b - \pi(1, r_b)) \\
 & b \equiv qP_h(h + i)
 \end{aligned}$$

A renting household's problem becomes:

$$\begin{aligned} V_j^R(\mathbf{s}) &= \max_{c, a', d} u(c, d) + \beta \mathbb{E}(V_{j+1}(\mathbf{s}')) \\ \text{s.t. } & c + a' + P_r d + b R_b = x + (1 - f_s) P_h (h + i) \end{aligned}$$

The model solution is computed on a finite grid space that approximates the true state space. The accuracy of the solution is improved when the distribution of points within this grid space are chosen carefully. As is the case in any standard model of consumption under uncertainty with borrowing constraints, the consumption policy function is increasing and concave in x . Approximations to the consumption function, then, benefit from clustering points in the x grid near zero. I use 50 grid points, distributed on the interval $[0, 85]$ using an inverse-exponential scaling function. Households with large loan to value ratios also exhibit significant curvature in their policy functions, suggesting that points in the q grid should be clustered near the maximum LTV ratio. I use 25 grid points, distributed on the interval $[0, \theta_b]$ using an exponential scaling function. As discussed in Section 5.2, I only allow households to purchase one size of house and investment property. This means the grid space for each of these state variables is $0, \underline{h}$. I use five grid points for the Markov chain representing the persistent component of income y , and I use Gaussian quadrature with five nodes to approximate the IID component of income.

Computation of Equilibrium

In the stationary equilibrium, two market clearing conditions must be satisfied: rental demand equals rental supply, and housing demand equals housing supply. To find the equilibrium, first define the excess demand functions:

$$\begin{aligned} ERD(P_r, P_h) &= \sum_{j=1}^J \left[\int \iota_j^D(\mathbf{s}) s_j(\mathbf{s}) d\mu_j(\mathbf{s}) \right] - \sum_{j=1}^J \left[\int (\iota_j^A(\mathbf{s}) + \iota_j^N(\mathbf{s})) i'_j(\mathbf{s}) d\mu_j(\mathbf{s}) \right] \\ EHD(P_r, P_h) &= \sum_{j=1}^J \left[\int (\iota_j^A(\mathbf{s}) + \iota_j^N(\mathbf{s})) (h'_j(\mathbf{s}) + i'_j(\mathbf{s})) d\mu_j(\mathbf{s}) \right] - \bar{H} \end{aligned}$$

Then define the sum over the squared deviations from each market clearing condition: $Z(P_r, P_h) = ERD(P_r, P_h)^2 + EHD(P_r, P_h)^2$. Notice that a zero of the function Z corresponds to simultaneous zeros of the two excess demand functions, ERD and EHD . I can then use a nonlinear minimization routine over Z to find the market clearing prices P_r , and P_h .

Finally, to help with calibrating the model I employ a trick inspired by Boppart et al. (2018). This involves replacing the housing market clearing conditions with one of the SMM moment conditions. Specifically, rather than calibrating the model by guessing values \bar{H} to match the observed homeownership rate, I solve for equilibrium by varying the house price P_h to match the homeownership rate directly. The market clearing housing supply \bar{H} is then backed out from the housing market clearing condition.